University of Alberta

The Examination of Community Level Economic Sustainability Indicators in Canada

by

Nancy Leake ©

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N Leake

A309 12015 25Ave
Edmonton, AB, T6J 4G6

Date: April 14, 2003

University of Alberta

Faculty of Graduate Studies and Research

The undersigned certify that they have read, and recommend to the Faculty of Graduate Studies and Research for acceptance, a thesis entitled: **An Examination of Community Level Economic Sustainability Indicators in Canada** submitted by Nancy Leake in partial fulfillment of the requirements for the degree of Master of Science in Agricultural and Resource Economics.

Dr. W.L. Adamowicz
(co-supervisor)

Dr. P.C. Boxall
(co-supervisor)

Dr. T.S. Veeman
(committee chair
& examiner)

Dr. C.G. Hickey
(committee member)

Dr. W.A. White
(committee member)

Date: April 14, 2003

ABSTRACT

The need for more accurate economic sustainability indicators within sustainable forest management has been suggested by a number of authors. A literature review helped to identify the most common and most respected indicators of economic sustainability. This study's main intent was to examine how increases in forest economic activity (expressed as forest dependence) affect these measures of economic well-being. The 1986, 1991, and 1996 Canadian census were used as the primary data sources with the census subdivision (CSD) as the unit of analysis. Frequency and distribution graphs were used to provide some insight into the changes in indicators over time, and correlation analysis was employed to examine correlations between the indicators and forest dependence. Within each time period, forest dependence was negatively correlated with median household income, and positively correlated with the unemployment rate, and the incidence of low income for people living in private households.

The empirical models in this study were specified as random effects panel regressions. These models showed that forest dependence was positively and significantly related to a CSD's unemployment rate and to the incidence of poverty for people in private households. Additional relationships were defined by examining the impact that other variables such as economic diversity, trade exposure, and aggregate demand have on indicators at the CSD level.

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1 INTRODUCTION

1.1 Research Problem

The World Commission on Environment and Development (WCED) of the UN cites sustainable development as "...development that meets the needs of the present without compromising the ability of the future generations to meet their own needs..." (Bartelmus, 1994). The general notion is that sustainable development can guide economic activity to maximize the overall benefits to present and future societies. The concept of sustainability, now viewed as a guiding tool in resource management, encompasses the environmental, economic, and social dimensions of the economy and the environment in which we live.

The Canadian Council of Forest Ministers (CCFM) created a set of criteria and indicators to guide sustainable forest management in Canada (CCFM, 1999). The need for more accurate economic sustainability indicators within sustainable forest management has been suggested by a number of authors. With economic systems, the challenge is to measure "well-being", analyze the distribution of well-being, and ensure that well-being is not declining (Adamowicz, 2001). Suitable economic sustainability indicators are normative, are consistent with theoretical concepts of well-being or "economic welfare", have the ability to be linked to management or policy options and can be predicted or forecasted. In addition, ideally these indicators should be measurable at relatively low cost, and be reliable such that repeated measurements of the same indicator achieve the same quantitative result (IISD, 2000).

Many researchers have incorporated economic sustainability indicators into their studies in attempts towards achieving economic sustainability.

1.2 Research Objectives

The intent of this study was to isolate some credible economic indicators and examine them in forest and non-forest dependent communities. The objective was to determine how forest dependence affects community level indicators such as incidence of poverty, the unemployment rate, income inequality and median household income. The study was also designed to investigate how other variables such as the trade exposure and economic diversity of a community and aggregate demand affect community level indicators. The national census is one source of information at a disaggregate level that, with some reorganization of the information, proves useful in understanding some of the economic dimensions of sustainability.

Data were extracted and derived from the Canadian census at the census sub-division (CSD) level for the years of 1986, 1991, and 1996. The indicators examined include median household income, income inequality (as measured by the Gini coefficient), trade exposure to exports and imports, economic diversity, the unemployment rate and the incidence of low income in private households. These indicators are among the most accepted indicators in the areas of income, equity and resilience.

Although this study retained as many of the census subdivisions (CSDs) as possible, special attention was paid to how the chosen indicators varied over time in CSDs deemed 'forest dependent'. The relationships between forest dependence and each

of the community level indicators provide insight into the causal factors associated with the indicator trends. Regression analysis was used to define relationships between forest dependence and individual variables with a view towards assessing the economic sustainability of an area.

1.3 Thesis Organization

This thesis is organized into three parts. Part 1 consists of Chapter 2. Chapter 2 provides a comprehensive review of the economic sustainability indicators found in the literature. They span four categories: measures of augmented national/regional income accounts, personal income and community equity measures which highlight distributional concerns, resilience measures that help to explain how well-being in a community changes in response to shocks to its economy, and a fourth group of economic and social indicators that include things such as community capacity and human capital. This chapter also discusses the evolution of indicators in sustainability assessments, the issues surrounding the scale of the analytical unit, and the importance of economy-wide assessments of sustainability.

Part 2 contains data collection details and descriptive statistics for a selected set of economic indicators. The methodology and manipulation used to compile the study's database from the census and other sources is described in Chapter 3. Chapter 4 presents descriptive statistics and preliminary analysis of the indicators. Each economic sustainability indicator's trends over time in forest and non-forest dependent regions is explored. These patterns are exemplified using frequency and boxplot graphs.

Correlation analysis was used to describe the relationships between forest dependence and the various economic indicators.

The final part, Chapter 5, focuses on the study's structural analysis. This paper discusses the specification of the study's economic models, as well as the results from the estimations. These models serve to uncover relationships between the indicators at the community level.

Chapter 6 provides a summary of the main research conclusions and policy implications, as well as suggestions for possible future research initiatives.

2 LITERATURE REVIEW[1]

2.1 Introduction

The concept of sustainability, now viewed as a guiding tool in resource management, encompasses the environmental, economic, and social dimensions of the economy and the environment in which we live. While each element is essential for building a sustainable path of development within sustainable forest management, little attention has been given to defining and measuring the concept of economic sustainability. In order to adequately measure and progress towards sustainability, one must have a solid understanding as to what economic sustainability entails.

Economic sustainability involves assessment of the market and non-market benefits for the economy and for the people in the area. This is intended to ensure that preservation of the productive capacity will leave future generations with a mix of goods and services that does not reduce their well-being. Thus, economic sustainability can be defined as non-declining well-being for citizens in terms of their ability to meet their basic needs, and in terms of satisfactory social conditions of the environment in which they live. From this definition, achieving economic sustainability may be difficult as the preferences of future generations are hard to assess. Thus, even using the best information available, decisions may be made with the values of present generations in mind. Nonetheless, many researchers have incorporated economic sustainability indicators into their studies in attempts towards achieving economic sustainability. This

[1] This review has been published as a Sustainable Forest Management Network Working Paper (2001-11)

chapter critically reviews some of the economic sustainability indicators currently used, in areas such as augmented income, equity and resilience.

2.1.1 Sustainability and the Need for Indicators

The concept of sustainable development arose from concerns about present and future resource use and environmental quality (Bartelmus, 1994). The general notion is that sustainable development can guide economic activity to maximize the overall net benefits to present and future society. However, attempts to derive one concrete definition have thus far proved to be elusive. The reason for this uncertainty could be that different economic, environmental, and social conditions in various local areas produces an enormous diversity of current and potential human living environments (Bell and Morse, 1999).

The World Commission on Environment and Development (WCED) of the UN cites sustainable development as "...development that meets the needs of the present without compromising the ability of the future generations to meet their own needs..." (Bartelmus, 1994). Although this definition has been incorporated in various international agreements and policy documents around the world, the fact remains that the implementation of sustainable development is difficult for our complex systems (Beckley, 2000). On the other hand, the current flexibility of the definition of sustainable development is appealing because attempting to apply a narrow definition across diverse human environments could be impractical and potentially dangerous (Bell and Morse, 1999). Another common definition of sustainability is non-declining well-being of a

"…representative member of society for millennia into the future…" (Pezzey, 1992). As Adamowicz (2001) stated, this non-declining well-being involves maintained or increased "satisfaction" or "utility" of market and non-market goods and services through time. Assessment of sustainability in any area depends on the operational definition employed and the criteria used for measurement.

A popular definition of sustainable development requires that natural capital be non-declining through time. Natural capital refers to any stock provided by nature such as minerals, forests, or groundwater (Pezzey, 1992). In regards to natural resources, the value is derived from their capacity to produce usable goods and services. Once this is recognized, discussions about substitutions and tradeoffs can ensue (Solow, 1992). The definition of natural capital implies one of two guides for decision-making. Strong sustainability requires maintenance of every kind of capital (natural, physical, social, human) so that alone, their levels are non-decreasing over time. This means that there is no substitution between categories of capital in production, and each capital's value is preserved. On the other hand, the concept of weak sustainability may be more realistic to achieve. It allows for substitution and technical progress between capital categories, as long as the value of the overall capital base (wealth) is maintained over time (Bartelmus, 1994). In their view, Acutt and Mason (1998) believe that sustainability is better interpreted in its weak form for policy-making. However, this weak sustainability definition is a narrow conception of what sustainability should accomplish. For example, it does not take into account intragenerational concerns such as income distribution, even though this in an important aspect of sustainable development (Hanley, 2000).

Sustainability has historically been applied to environmental systems, but a more holistic interpretation may be possible if sustainability is applied to economic systems (Beckley, 2000). A holistic conception of sustainable development should contain three critical sub-elements: a growth element, a distributional element, and an environmental element. The growth component analyzes the productive capacity of the economy. This should also include non-market values, and depreciation of environmental assets. The distributional component tries to characterize the impacts of economic growth on poverty rates and concerns of income inequality. Finally, the environmental element contains ecological and environmental policies and ideas necessary for sustaining economic growth (Veeman, 1989). Acutt and Mason (1998) remind us that we cannot aim for sustainability of all things; there must be tradeoffs between various components of human welfare. However, understanding tradeoffs requires the development and application of valuation methods that ensure the most sensible tradeoffs are being made.

The assessment of sustainability is often accomplished with the use of indicators. Indicators attempt to simplify complex information for easier comprehension. They also quantify this information "...so significant changes or differences in the larger phenomena are more readily apparent and can be compared..." (Toman, Lile, and King, 1998). In order to manage a phenomenon, it must be measured. Indicators allow us to identify benchmarks so that economic systems can be manipulated to move the benchmarks in the desired direction. However, this requires that the desired direction be determined for each indicator in order to create a positive change (Beckley, Parkins, Stedman, 2002). In a 1995 discussion document, the UN Commission for Sustainable Development reminded governments and NGOs that Agenda 21 calls for the use of sustainable development

indicators. These indicators are meant to assess sustainability in social, economic, and environmental systems. The UN wanted a consistent sustainability measure for international comparisons with the potential for individual national flexibility (Hanley, 2000).

Although groups worldwide have tried to set sustainable development goals, there has been less effort in the selection and design of sustainability indicators. This is unfortunate, as the use of indicators can provide policy-makers with guidance and a measure for tracking sustainable development.

Good economic sustainability indicators are characterized by a number of criteria. First, these indicators should be positive measures with normative implications, so as to adequately assess sustainability concerns. This usually involves a value judgment, where the indicator would suggest 'what ought to be'. Second, they should be consistent with theoretical concepts of well-being or "economic welfare". Next, a good indicator should be linked to management or policy options. In addition, the quantitative value of these indicators should be able to be predicted or forecasted. For example, the International Institute of Sustainable Development's (IISD, 2000) list of indicator requirements suggests that indicators should be based on time-series data which reflect the need for examining trends of indicators over time. This allows one to see the direction an economy or community is heading towards. The indicators should be conducive to linkages with models for potential projections, and other hypothesis testing. Finally, sustainability indicators should be measurable at relatively low cost and reliable such that measurements taken of the same indicator (at the same point in time) by two or more researchers would give the same result (IISD, 2000).

If sustainable development is the planning goal, identification of suitable indicators is necessary for adequate policy development (Gustavson, Lonergan, and Ruitenbeek, 1999). Economic systems provide the basis for identifying and measuring economic sustainability indicators. When studying economic sustainability, however, the scale of the analysis, or size of the region in question is a critical component of the sustainability assessment.

2.1.2 The Question of Scale

Within the sustainability literature, there is considerable debate on the scale at which sustainability should be assessed. Scale is an important issue in measuring economic sustainability, just as it is in biological assessment (Adamowicz, 2001). Sustainability measures often differ by the sociopolitical jurisdiction focus, whether it is a country, province, or individual community. The scale of the indicator will be related to the policy or management context. Many indicators of sustainability have been developed and measured at large scales (e.g. CCFM, 1997). National level policy assessment may be based best on the use of national indicators. Measurement at this macro level is adequate for general well-being assessments, but it may not identify communities in which well-being is particularly high or low. Also, linkages between forest management practices and social and economic factors will not be apparent at such large scales. Thus, some researchers advocate that a micro level approach to sustainability is more appropriate (Haynes and Mohomed, 1999).

The debate over spatial scale for sustainability measures is largely rooted in the interdependencies between sociopolitical levels. Many regional and national long-term environmental, social, and economic functions are influenced by decisions made at the

community level. Thus, broad concepts of sustainability stem from many smaller combined community effects. However, the community level decisions are not made within isolation of one another. Communities are often dependent on policies and events occurring beyond their borders (Toman *et al*, 1998). There are many environmental, social and economic linkages within a region that are necessary for each community's integrity and stability. Due to these significant interdependencies, one could argue that a region is a more accurate level at which to study and assess sustainability. It may be necessary, then, to use standardized measurements to enable comparisons between communities for aggregation up to the regional level (Force and Machlis, 1997).

When further justifying scale choice, it is necessary to keep in mind that many general indicators (or indicators on a larger scale) usually lack the ability to forecast conditions into the future. If an indicator gives a good picture of current conditions, but cannot be projected or measured through time, it may not be very useful in assessing the path towards sustainability. Thus, the indicator should be able to be modeled in a dynamic analysis. An effective model depends heavily on the scale of the analytical unit. Thus, for desirable indicators that can be forecasted, scale choice should be exercised with caution. In addition, even if community level assessment is chosen as the preferred scale, the indicator data may not be supported at this level. At small micro levels, data may be hard to access, expensive, or simply may not exist. At this point, a more aggregate scale such as regional or national sustainability may have to be used for more reliable results (Gustavson *et al*, 1999).

Fortunately, the Canadian national census (taken every five years) provides data on numerous indicators at the census subdivision (CSD) level. This analytical unit can be

approximated as a community. The Canadian census and its focus on the CSD level form an important basis for the study in this thesis on community level economic sustainability indicators.

2.1.3 Canada's Background on Criteria and Indicators

The inception of indicators in the Canadian context was heavily influenced by innovative international work. At one of its regular meetings in 1992, the UN Conference on Environment and Development (UNCED) emphasized the importance of sustainable forest management (SFM) in furthering sustainable development. The adoption of the Statement of Forest Principles and Chapter 11 of Agenda 21 established the need for the development of criteria and indicators for the implementation of SFM. With the European countries working on their own criteria and indicators under the Helsinki Process, Canada launched its own initiative for other temperate and boreal countries. The Working Group on Criteria and Indicators for the Conservation and Sustainable Management of Temperate and Boreal Forests, now named the Montreal Process, was formed in 1994 to develop a set of international criteria and indicators to guide SFM (Montreal Process Working Group, 1997). These indicators would encompass the environmental, social and economic facets of Canada's forested regions. Since then, seven other international working groups for the development of criteria and indicators have evolved, all under different pressures. All eight groups attempted to produce criteria and indicators for the international, national, sub-national, and forest management unit levels. Due to interaction between the working groups, all agree on the fundamental criteria used as a basis for SFM (CCFM, 1999).

Canada regards the Montreal Process criteria and indicators as important international policy tools to regulate and manage the world's boreal and temperate forests in a sustainable manner. However, it had already become apparent that the country needed its own national indicators specific to Canada's unique forest attributes (CCFM, 1997). In 1992, the Canadian Council of Forest Ministers (CCFM) begun the process of developing SFM criteria and indicators. CCFM used present scientific knowledge as a basis for choosing indicators so they could be implemented at the national, sub-national, regional and local scales. The 1995 document, *Defining Sustainable Forest Management: A Canadian Approach to Criteria and Indicators* outlined a framework of 6 criteria and 83 corresponding indicators that attempted to capture the value and importance of Canada's forests (CCFM, 1999).

Due to the fact that the Montreal Process criteria and indicators were created in this same time period, the CCFM modeled their indicators to parallel those in the Montreal Process. The CCFM criteria for SFM in Canada are given in CCFM (1997):

Criterion 1: Conservation of Biological Diversity
Criterion 2: Maintenance and Enhancement of Forest Ecosystem Condition and Productivity
Criterion 3: Conservation of Soil and Water Resources
Criterion 4: Forest Ecosystem Contributions to Global Ecological Cycles
Criterion 5: Multiple Benefits of Forests to Society
Criterion 6: Accepting Society's Responsibility for Sustainable Development

The CCFM criteria are consistent with Criteria #1-6 in the Montreal Process. The seventh Montreal Process criterion relates to the country's overall ability to facilitate SFM in conjunction with the indicators in criteria #1-6. This corresponds to some of the CCFM indicators in criteria #5 and #6. A 1996 formal comparison of the CCFM and

Montreal Process frameworks indicated an 80% similarity (CCFM, 1999). Whereas the Montreal Process is an international framework, the particular implementation of CCFM criteria and indicators reflects the unique nature of Canada's forests and helps to define SFM in a Canadian context (Montreal Process Liaison Office, 1997). Thus, Canada partially uses the CCFM indicator framework to report on their national implementation of the Montreal Process. Beckley *et al* (2002) criticize the CCFM indicators for the fact that the desired trends for its indicators were never explicit in the CCFM documents.

Nevertheless, the Montreal Process and CCFM criteria and indicators were both created using the best national information available at the present time with regards to SFM. However, the definition and progress towards SFM is an evolving process needing continual refinement. Both frameworks recognize the need for future revision to the criteria and indicators. Canada acknowledged that its implementation of the Montreal Process criteria and indicators would "...require continuous refinement as science evolves, public values change, and new knowledge of forest ecosystems is acquired." (Montreal Process Liaison Office, 1997). This was reflected in a recent CCFM report (CCFM, 1999). Due to the new scientific information and availability of data, the concept of SFM has changed, thus the CCFM felt that the indicators would most likely need to be modified as well.

The indicators of economic sustainability can be found in CCFM Criteria #5 and #6 (CCFM, 1997). A CCFM Evaluation Committee (CCFM, 1999) made recommendations under these criteria that are of interest to this paper, as they portray the need for new economic sustainability indicators. For example, throughout criteria #5 and #6, the committee stressed the need for augmented income measures like green GDP.

This would permit the inclusion of non-timber values and other environmental non-market goods to give a more accurate measure of wealth (under weak sustainability). The committee also proposed that the new measures should include community characteristics such as social capital measures and unemployment levels (CCFM, 1999). This could help expand the concept and measurement of sustainability.

The Evaluation Committee made recommendations for nearly all of the 83 environmental, social, and economic indicators of sustainability (CCFM, 1999). However, the economic sustainability indicators are of the most interest for the purpose of this review. The need for more accurate economic sustainability indicators within sustainable forest management has also been suggested by a number of authors. As each has their own opinion of sustainability and expertise in different fields, the suggested economic indicators are varied. However, an obvious consensus has emerged from the suite of suggested indicators – the CCFM set of indicators inadequately measure the impacts forest dependence has on residents at the community level. Not only does CCFM fail to specify the desired trends of its indicators, but it lacks basic community level indicators that more adequately measure the economic sustainability of an area.

Instead of using forest dependence as a yardstick for growth, the study in this thesis uses forest dependence as an exogenous variable in random effects panel regressions. In doing so, it sets the stage for the examination of <u>how</u> forest dependence affects indicators such as the incidence of poverty, the unemployment rate, income inequality, and median household income at the community level. This study also examines how the trade exposure and diversity of a community, as well as aggregate demand, can affect these income, equity, and resilience indicators. It is the lack of such

important indicators that makes the CCFM framework unrealistic for measuring economic sustainability.

The challenge behind economic sustainability is to develop policies that support economic growth while improving environmental quality and alleviating poverty and equity concerns (Veeman, 1989). A further challenge is to utilize broader conceptions of well-being and wealth to ensure that non-market environmental components are incorporated appropriately. With economic systems, the challenge is to measure "well-being", analyze the distribution of well-being, and ensure that well-being is not declining. This explains why this analysis of economic sustainability is often divided into four approaches: (1) augmented national/regional income accounts that cover the measurement of well-being including market and non-market goods, (2) personal income and community equity measures which highlight distributional concerns, (3) resilience measures which help to explain how well-being in a community changes in response to shocks to its economy and (4) a group of social indicators, such as community capacity and human capital which often accompany economic indicators in studies of sustainability. All of these measures attempt to describe the sustainability of the economy or community, rather than any specific industrial sector like the forest sector or energy sector (Adamowicz, 2001).

2.2 Augmented Income Measures

A popular economic indicator at an aggregate level has been the Gross Domestic Product (GDP). GDP is appealing because the system of national accounts is rigorously standardized across countries, provinces, and to a lesser extent, regions. A measure of

economic well-being that is frequently employed is GDP per capita. A major problem with this measure is that the system of national accounts ignores the values of services of unpriced environmental assets. Thus a relatively new class of economic indicators involves "augmenting" traditional economic measures like GDP with values of 'non-traditional' income to provide a more realistic picture of the economy. Contemporary augmented income measures are loosely separated into two categories: green national product, and genuine savings.

2.2.1 Green National Product

Green national product, also called green accounting, supplements indicators of economic activity with considerations relating to environmental assets and services. Thus, the green national product tries to account for the value of non-market resources, and changes in environmental stocks and services. This is part of a broader development of comprehensive economic indicators. These indicators reflect the fact that economic and social welfare depends on economic activities and 'near-market' and non-market activities. *Nature's Numbers: Expanding the National Economic Accounts to Include the Environment* (hereafter called *Nature's Numbers*) provides a review of the basic theoretical principles of green accounting (Nordhaus and Kokkelenberg, 1999). The book addresses the question as to whether the U.S. National Income and Product Accounts (NIPA) should be expanded to incorporate environmental and natural resource activities. *Nature's Numbers* reports that augmented national accounts "should be" a high priority. Ideally, the development of non-market accounts would account for the value of non-market natural resources (to measure subsistence values), non-market work, environmental impacts, the use of people's time, and the investments in human capital.

However, due to current knowledge and methodology, recording resource and environmental flows in satellite environmental accounts may be a wiser, realistic goal at the present time. *Nature's Numbers* summarizes green accounting theory with respect to subsoil mineral assets, and renewable and environmental resources (including resources for subsistence). As well, it discusses the potential problems associated with valuation. In relation to forest resources, augmented accounting includes adjustments to production accounts, and forest asset accounting. Necessary adjustments to the traditional accounts include valuing the benefits and costs associated with timber income, the values of near-market forest products, and contributions to household production, environmental services, and public goods (Nordhaus and Kokkelenberg, 1999).

Some authors attempt to calculate green national product for the economy as a whole, while others incorporate green accounting into one facet of the economy. For example, Hultkrantz (1992) analyzed the extension of Sweden's national account of income from forest resources in 1987. He focused on the inclusion of non-marketed or partially marketed forest products and environmental stocks. The augmented measure of national forest income had 11 main components: timber production, berries, mushrooms, game, recreation, biodiversity, hydrological effects, carbon fixing, depletion of exchangeable base cations, nitrogen leaking, and reindeer forage. The inclusion of berries, mushrooms and game is meant to capture subsistence values for individuals who rely on the forests for such non-market products. Hultkrantz (1992) stresses that this augmented measure must include the value of change in resource stocks in order to be a consistent measure of welfare. However, changes in asset price should not be included; the changes in resource stocks should be valued at marginal net prices. Even though

information from the supply side is more readily available, Hultkrantz (1992) believes that environmental assets and services should be evaluated from the demand side. (Supply side evaluation can provide large overestimates of the true value). Cost measures from the demand side should be based on the utility derived from these costs. The Hultkrantz (1992) study uses evidence of utility in the form of environmental targets and areas where critical load levels have been exceeded. Thus, Hultkrantz (1992) is limited by his own criteria to only evaluate environmental resources whose critical load levels have been surpassed, and those which are considered environmental flow services (timber and non-timber products). Thus, this augmented national income from forest resources does not include all of the services provided by the forest, such as non-use values.

A study that incorporates economic depreciation into sustainability analysis is Tamai (2000). This author examined the sustainability of Canada's forest sector from 1970-1993 using the weak sustainability indicators of adjusted forest sector net domestic product and net investment (which is equivalent to the net savings approach). These weak sustainability measures include the appreciation or depreciation of forest resources and assets. To calculate these indicators, Tamai (2000) first estimated the economic depreciation of Canada's timber resources. These estimates were limited to the wood used for manufacturing timber; thus, there were no estimates to correct for non-market goods and services related to the forests. The author admits that the subsequent analysis of the social values associated with forest assets will understate the actual gains and losses. Although there is no consensus on how economic depreciation should be

measured, Tamai (2000) chose to obtain the estimates of economic depreciation through the net price approach, and the Vincent-Hartwick approach.

The net price approach is the product of the net annual change in timber stock and the Hotelling's rent. Hotelling's rent, or the net price, represents the economic depreciation of a resource (Tamai, 2000). Tamai (2000) also presented a second net price scenario that incorporated the growth stock effect into the net price calculations. Tamai (2000) found that the two net price scenarios presented almost identical results and that calculations of total timber rent (only gross annual depletion) overstated economic depreciation values compared to the net price approach.

On the other hand, the Vincent-Hartwick approach accounts for the age effect – the number of years until a forest reaches maturity. This approach values mature forests differently from immature forests, thereby accounting for the opportunity cost of letting the immature forests grow to maturity and the quality differences among the age-class distribution of the timber stocks. Economic depreciation under the Vincent-Hartwick approach is calculated as the sum of the per hectare appreciation of immature forests and the per hectare depreciation of mature forests (Tamai, 2000). The fact that regulatory regimes may limit harvests was not accounted for in the calculation of the optimal rotation ages, so Tamai (2000) developed three different scenarios under the Vincent-Hartwick approach. Scenario 1 represented a situation where all existing standing timber and the capitalized forestland values were all calculated at 161 years, the oldest age-class in the sample. Scenario 2 also calculated the value of harvesting standing timber at 161 years, but determined the capitalized land site values by the estimated optimal rotation ages. Scenario 3 incorporated regeneration costs into the estimates of the land site values

and the optimal rotation ages. Across all scenarios, Canada's timber resources were shown to be consistently appreciating before 1977/78, and consistently depreciating after 1982. The economic depreciation estimates under the Vincent-Hartwick approach showed that calculations of total timber rent, and even estimates under the net price approach, overstated the value of economic depreciation. This is most likely attributed to the fact that the Vincent-Hartwick approach accounts for the increasing capitalized value of immature forests (Tamai, 2000). However, even though this approach may be more appropriate for measuring economic depreciation, Tamai (2000) admits it is considerably more complex.

Using the economic depreciation estimates, Tamai (2000) was able to calculate weak sustainability measures of adjusted forest sector NDP and net investment to assess the sustainability of Canada's forest sector. Adjusted net product is the sum of consumption, the change in value of natural capital, and the change in value of human-made capital (Adamowicz, 2001). The adjusted forest sector NDP under the different scenarios of economic depreciation was compared to conventional domestic product (GDP and NDP) for Canada's forest industries, and little difference was found during most periods of 1970-1993. The net price adjusted NDP estimates were consistently lower than conventional NDP. Adjusted NDP under the Vincent-Hartwick approach was higher than conventional NDP for most of the 1970s and in 1982/83. This difference is due to the fact that the Vincent-Hartwick calculation can show the appreciation that occurred during these time periods. Weak sustainability requires an overall non-declining capital stock assuming unlimited substitutability between natural capital and

man-made capital. Although the trends are not clear, the adjusted NDP measures may narrowly suggest an upward trend, indicating sustainability (Tamai, 2000).

The weak sustainability measure of net investment was also used to assess the sustainability of Canada's forest sector. In this case, net investment is calculated by subtracting the estimated value of depreciation of timber resources and man-made capital in the forest sector from the total investment in the forest sector. Net investment for the forest sector was determined by including the estimates of economic depreciation previously obtained in the analysis. Net investment calculated under the net price approach showed continuous negative investment throughout the period of 1970-1990. The Vincent-Hartwick approach resulted in net investment values fluctuating between negative and positive throughout the same time period. Although difficult to make a firm conclusion, these net investment results suggest that the Canadian forest sector was unsustainable from 1970-1993. Hence, insufficient funds were reinvested in this sector to compensate for the depreciation occurring in the forest sector (Tamai, 2000).

A smaller scale attempt in this area can also be found in Gravel, Lawrance, and Ecclestone (1995). These authors provide a comparison of the present value method and the net price approach in terms of measuring the value of Ontario's timber resources. Gauthier, Saphores, and Bouthillier (2000) also attempted to include forest resources in provincial accounts. This group of researchers from Laval University developed a forest resource account for the Haut-Saint-Maurice region in Quebec, Canada.

The above forest resource accounts differ in their inclusion of non-market values. However, natural resource accounts that incorporate both natural capital depletion and

non-market values will serve as an important tool for forest management and provide an index of socioeconomic sustainability (Adamowicz, 2001).

As seen above, economic depreciation requires adjustments to be made to income measures. This idea is further emphasized in Haener and Adamowicz (2000). These authors modified the net income measure within a forest resource account for a forest in northern Alberta to account for price and fire risks. These two types of risk represent potential appreciation or depreciation of forest resources. In order for net income to be a suitable indicator of sustainability, it must account for risk, which can change future net income dramatically. Haener and Adamowicz (2000) cite Brekke (1997) as stating that the uncertainty of future rents prevents a guaranteed sustained level of consumption into the future. Instead, one should strive to attain a non-declining expected value of income flows over time. Future rents can be affected by changing market and environmental conditions, which translate into many risks. However, Haener and Adamowicz (2000) only examine two possible types of risks, price and fire, as these were deemed potentially significant to the study area.

As an alternative to reformulating the deterministic welfare indices relating to net income measurement, Haener and Adamowicz (2000) chose to use simulation exercises to show how risk affects sustainable income. Haener and Adamowicz (2000) used the depreciation approach and the wealth approach to calculate adjusted net income estimates using the stock changes implied by the simulations. The net income estimates under the depreciation approach fluctuated sharply over time compared to the net income generated under the wealth approach. This is due to the fact that the depreciation approach overweighs current declines in stocks, as it does not account for the forest's ability to

regenerate in the future. On the other hand, the wealth approach values current stock changes by using information relating to revenue flows in the future. Thus, Haener and Adamowicz (2000) conclude that the wealth approach is more appropriate in calculating net income for renewable resources that are subject to risk. Under the wealth approach, Haener and Adamowicz (2000) also found that price risk played a more dominant role than fire risk in affecting net income estimates. The authors admit that the simulations in this study did not account for all of the necessary factors to provide exact estimates of the net income adjustments that are needed. However, their results emphasize the need to incorporate risk into net income calculations to accurately assess the sustainability of the income flows in an area (Haener and Adamowicz, 2000).

In developing an augmented economic measure, Harrison (2000) took a different approach. She wanted to develop a framework that could link the economic, environmental, and social spheres of the economy. The basis of the new framework was the System of National Accounts (SNA). The SNA is a time-series framework, which is ideal when trying to evaluate concepts such as sustainability. Also, the SNA has a common numeraire of money. This is also ideal; economic alternatives are often compared through monetary channels, which in turn impact choices in the social and environmental components of the economy (Harrison, 2000).

While Harrison (2000) chose a monetary framework for an augmented economic measure, Toman *et al* (1998) suggests avoidance of the problems associated with monetary valuation by developing a framework based on physical flows instead[2]. Their proposed framework begins with an evaluation of the total net output of goods for

[2] Application of a national accounting system based on physical flows that incorporate environmental concerns can be found for Norway and Denmark in Kristrom (1995).

resource extraction, consumption, intermediate production, and capital formation. These values are determined both inside and outside the community being examined. Total imports of natural resources, produced commodities and capital goods are also included in the framework. Total income generated by the community, and net changes in the produced capital stock are added to the above components. It is also important to account for the changes in the natural resource stocks. Similarly, environmental pollutants should also be measured for their impacts on environmental quality and ecological functions. While Toman *et al* (1998) are satisfied with a framework that includes all of the above components, they admit that two problems impede its implementation. First, Input-Output models have difficulty properly accounting for the important roles played by natural resources and the environment. Second, regional environmental economics modeling has a comparable lack of capacity (the ability for substitution in maintaining capital)[3]. Although this framework still includes many necessary components for an adequate augmented measure, it requires a set of criteria to evaluate the augmented framework (Toman *et al*, 1998).

Most researchers now agree that traditional measures of economic activity such as GDP/GNP no longer provide an adequate value of the economy. In attempting to achieve economic sustainability, new augmented measures must be utilized that incorporate environmental and even social concerns into the big picture. These new measures should account for non-market resources (including those used for subsistence), depletion of resources (changes in environmental stock), and degradation of the environment (changes in environmental services). The addition of subsistence values may be particularly

[3] There have been recent advances in this area through green CGE models. For an example of this work, see Patriquin, Alavalapati, Adamowicz, and White (2001).

important in certain rural and aboriginal communities where the "income" of many residents is heavily supplemented by non-market forest resources (such as berries, and game). Inclusion of these values holds promise in producing a more accurate portrayal of the state of the economy.

2.2.2 Genuine Savings

Genuine savings involves measuring the creation and maintenance of wealth. Savings and investment have always played a large role in economic theory. Thus, it is surprising that the depletion of resource stocks and environmental degradation have only recently been incorporated in measuring national savings. The augmented measure of genuine savings can be used as an economic sustainability indicator (Hamilton, 2000).

Pearce and Atkinson first introduced genuine savings in 1993. Since then other researchers have adopted and expanded this concept. Some of the contributions include incorporation of technological change and appreciation of human capital, improved monetary valuation of environmental depreciation, and international trade applications (where sustainability is 'imported' or 'exported') (Hamilton, 2000).

According to Hamilton, the calculation of genuine savings consists of investment in human capital as well as produced assets, less the value of pollutant accumulation, and depletion of natural resources. Thus, negative genuine savings is an indication that future utility is less than current utility over time on a certain optimal path (Hamilton, 2000). Another way of defining genuine savings, also called genuine investment is given in Dasgupta (2001). This author explains that the theory behind genuine savings defines a country's wealth as the sum of the social worth of manufactured capital, natural capital, human capital, and research and development. Together, all these components comprise

the capital base of an economy, and provide an index of well-being based on wealth. Thus, genuine savings is a measure of a nation's opulence. Dasgupta (2001) points out that while a discrete figure for a nation's wealth (or genuine savings) is not very meaningful, differences in genuine savings over time provides a way of measuring sustainability. For example, under genuine savings, a nation's wealth in the current period is equal to the wealth in the previous period plus that period's net investment. Thus, the wealth of a nation increases only if there is positive net investment in the capital base (Dasgupta, 2001).

There are many advantages to using genuine savings as a sustainability indicator. First and foremost, genuine savings is a more accurate measure of sustainable well-being than traditional measures such as Gross National Product and Net National Product. For arguments supporting this theory, see Dasgupta (2001). The measure of genuine savings also has a reference point; any measure below zero indicates an unsustainable path of development. Like green national product, genuine savings incorporates economic, environmental, and social concerns. Savings and conventional asset depreciation represent economic behavior, while the environmental concerns are embodied in measures of environmental depreciation and environmental damage. Social concerns are more difficult to incorporate into measures like genuine savings. However, there have been efforts to include estimates of human capital appreciation and inter-personal concern. Another important feature of genuine savings (which is lacking in other sustainability indicators) is that it allows for a detailed analysis of why sustainability may or may not exist. For example, genuine savings can report to what extent potential nonsustainability is due to excessive depreciation in environmental assets, an insufficient

savings rate, or under-investment in human capital. Genuine savings accounts for imports and exports and how they affect sustainability. This is also absent in most sustainability indicators (Pearce, 2000).

There are some disadvantages for using genuine savings as a sustainability indicator. Pearce (2000) believes that genuine savings is merely a variant of green accounting, and he notes that green national accounting has yet to have a significant impact on policy change. He also admits that other drawbacks include that genuine savings is a weak sustainability indicator and that environmental and social assets must be valued in monetary terms (Pearce, 2000).

Hamilton (2000) also stresses that a high level of genuine savings does not necessarily mean a smooth development path. For example, in Southeast Asia in 1997/98, genuine savings were positive, but many investments were yielding extremely small returns. Thus, genuine savings must not only be evaluated on the level of saving, but on the quality of investments as well (Hamilton, 2000).

Since it is no longer acceptable to exclude environmental and social concerns in economic decision-making, both green national accounting and genuine savings hold promise as economic sustainability indicators. It is also important to note that when estimating augmented income or any other measure of well-being, they should be reported in per capita terms because this information can be used to determine if "well-being", on average, is increasing or declining. However, using only augmented income measures as an indicator of well-being is limiting. One reason is that these measures assume that the aggregate share of income devoted to accumulation of stocks (including

unpriced assets) is optimal (see Osberg and Sharpe, 2001). Augmented income measures also ignore the influence of income distribution or economic insecurity.

2.3 Income Measures

In a 1995 document *Ontario beyond tomorrow: ideas for building a sustainable society*, the Ontario government chose average family income as one indicator for measuring the province's progress towards sustainability. (Ontario Round Table on Environment and Economy, 1995). This measure has been used widely in the past, as it hints at how big the 'income pie' is in a community. However, several researchers have questioned the reliability of results based on average income. Krugman (1994) points out that average income masks the distribution of income within a community or region. Thus, income distribution and poverty rates must be examined in conjunction with average income to give a more accurate picture of well-being in an area. Median income may be a more reliable distributional indicator. In contrast to average income, median income gives information on how the 'income pie' is divided in a community. If a region's income increases, but the benefits flow mostly to upper income families, average income will increase, suggesting a positive benefit to the whole area. However, median income may not increase, thereby reducing false positive conclusions (Krugman, 1994). Therefore, median income is a more robust indicator of income than average income as it is less sensitive to the influence of a small number of high values.

Both Beckley (2000) and Force and Machlis (1997) are advocates for the use of median income as an indicator in assessing sustainability. Median income has been examined at the community or regional level. These scales are probably the most

appropriate for determining the distributional impacts from economic activity. Although median income may prove to be better than average income, concerns have been raised about its use as an adequate indicator as well. Thompson (1997) suggested that median income values could be misleading as it ignores specifics about the top and bottom incomes. Toman *et al* (1998) are also concerned that median income presents only a partial picture of how the local economy affects income distribution and the well-being of the people. Their argument is that "...at the local level, it is important to examine the spatial decomposition of important economic flows..." (Toman *et al*, 1998). For example, is the region's income high due to local economic flows or do income supports or tax breaks exist that may distort the economy's actual impact on income? (Toman *et al*, 1998). Also, even though median income was used as an indicator in Beckley (2000), the author warns that its interpretation should be taken with care. The traditional measures of income do not take into account any non-wage subsistence activity that may exist within an area. Such activity may be highly valued by the resident people. In such cases, it is likely that traditional measures of income and income distribution would be inappropriate indicators for measuring sustainability. Instead it would be necessary to try to capture these non-market values with measures of augmented income. Despite these concerns, median income is still often used as an economic sustainability indicator.

2.4 Equity Measures

It is recognized that the concept of welfare depends not only on individual income measures, but also on the inequality of incomes (Osberg and Sharpe, 2001). However, it is very difficult to specify the relative weights to be applied to these features of an

economy to assess economic well-being. One reason is that the measurement of inequality depends on the relative value which an observer places on the utility of individuals at different point along the income distribution (Atkinson, 1970). For example, a Rawlsian[4] would only gain utility by observing positive changes in the well-being of the least well off in society (i.e. the poor). For others, positive weights would be sought for income gains of the non-poor, or negative weights may be applied to inequality among the non-poor. Thus, two areas of indicators could shed some light on the issue of well-being. The first is a measure of the distribution of income or some measurement of income inequality. The second involves indicators on the extent of poverty.

2.4.1 Income Distribution

In assessing sustainability, it is important to account for the distributional consequences of economic activity, rather than just measuring the economic net benefits in the region (Toman *et al*, 1998). Communities are usually comprised of very diverse populations; as such, these economic benefits may not be equally distributed (Beckley, 2000). This explains why income distribution measures are advocated as empirical measures of economic well-being. One disadvantage to using income distribution as a sustainability indicator is the fact that it is difficult to transform it into a normative measure (Adamowicz, 2001). In other words, there isn't a concrete yardstick that reports how much income inequality is acceptable. However, there are still many researchers who use income distribution as a sustainability indicator. There are many different ways

[4] A Rawlsian is someone who wishes to maximize the welfare of the minimum members of society. This idea has its roots in John Rawls treatise "A Theory of Justice" (1971: Harvard Univ Press).

to measure income distribution. However, each measure has its pros and cons which make it difficult to advocate for one standardized indicator of income distribution.

Social Accounting Matrix (SAM) models can depict how wealth is distributed. These models account for the interaction between the economic and social facets of the economy. Alavalapati, Adamowicz, and White (1999) used SAM models to examine the economy-wide impacts of various scenarios for the forest industry. These researchers were interested in how these simulated expansions and contractions in the forest sector would impact the distribution of income among three household income groups. SAM models were used to capture the multisectoral direct and indirect effects of the proposed changes. Alavalapati *et al* (1999) found that the changes had larger impacts on the high income household group than on the low income household group. The high income group reaped more of the benefits of expansion in the forest sector, and a contraction in the forest sector negatively impacted the high income group more than the low income group. This study further indicated through a price model that additional costs or taxes associated with environmental regulation and sustainable forest management will affect low income households more than high income households. These impacts from changes in the economy can be interpreted as shifts in the income distribution (Alavalapati *et al*, 1999).

The distributional impacts of production changes within a region, as indicated by SAM models can also be found in Leatherman and Marcouiller (1996). The allowance of various linkages through SAM models helps in determining impacts and how they manifest in various indicators.

Another measure of income distribution is the Gini coefficient of inequality. The Gini coefficient "...measures the extent to which the distribution of income (or, in some cases, consumption expenditures) among individuals or households within an economy deviates from a perfectly equal distribution." (United Nations Development Programme, 1999). The World Bank Group (2000) cites Gini's original 1912 definition as:

$$\text{Gini} = \frac{1}{2n^2\bar{y}}\sum_{i=1}^{n}\sum_{j=1}^{n}|y_i - y_j| \qquad [1]$$

where n = the number of individuals in the sample, $\bar{y}$ = the arithmetic mean income, and y_i = income of individual i, $i \in (1,2,\ldots,n)$. The Gini coefficient can take values between 0 (perfect equality) and 1 (complete inequality) (World Bank Group, 2000). This single number is easy to calculate and understand and income data at any scale can be used. Thus, the Gini coefficient can detect distributional changes in the middle of the income spread as well as at either extreme (Thompson, 1997). The Gini coefficient is also considered a robust measure of inequality, as it meets the desirable conditions for such a measure, including scale independence. This characteristic means that the Gini coefficient is independent of the units of measurement of income. This enables comparisons to be made across distributions (Prus, 2000). For example, the 1994 Gini coefficient of after-tax income in the US (0.387) was much higher than that of Canada (0.287) suggesting that income inequality was much higher in the US than in Canada in 1994 (Osberg and Sharpe, 2001). Thus, the Gini coefficient is a common indicator for income distribution and it can be set in a model context for perspective and specific interpretation.

Chevan and Stokes (2000) analyzed the effects of industrial restructuring and changing population composition on changes in the distribution of income for families between 1970 and 1990. The authors wanted to test whether de-industrialization led to increased income inequality. Their study spanned 784 public use microdata areas and metropolitan areas. The Gini coefficient represented family income, rather than individual income, as this unit of analysis was thought to best determine an individual's lifestyle. Chevan and Stokes (2000) used the change in employment share across six sectors as a key independent variable. The authors found that decreases in the share of manufacturing in an area, and shifts in employment towards the service sector increased income inequality (as measured by the Gini coefficient). Most of this increase in inequality was attributed to the shifts in income in the lower quintiles. Chevan and Stokes (2000) also found that increases in unemployment increased income inequality, while employment growth caused a decline in income inequality.

Sharpe and Zyblock (1997) also explored the relationship between unemployment and income inequality in Canada. The authors wanted to determine the impact of macroeconomic performance in Canada from 1975-1994 on family income distribution. The Gini coefficient acted as a proxy for family market income, which is income obtained before transfers. Income inequality was found to be highly dependent on the business cycle and other structural factors. A strong positive relationship was detected between unemployment rates and income inequality. Sharpe and Zyblock (1997) concluded that roughly 1/3 of the total increase in the Gini coefficients from 1975-1994 could be attributed to increases in the unemployment rate.

The above models by Chevan and Stokes (2000) and Sharpe and Zyblock (1997) offer promise in being able to predict indicators through time. This may be desirable in determining an economically sustainable path of development.

Gini coefficients have also been used as a measure of income inequality to test the Kuznets inverted-U hypothesis. This theory postulates that income distribution becomes more unequal with development until the country's economy reaches a point at which income distribution becomes more equal (Thornton, 2001). Thus, the presence of a Kuznets curve can detect periods of economic growth where the level of income inequality is high (undesirable for sustainability concerns). Using comparable real GDP per capita data, income quintiles, and the Gini coefficient for 96 countries, Thornton (2001) found that the Kuznets relationship between development and income inequality did in fact exist. However, there are others that are skeptical about the ideas surrounding this theory.

When examining income distribution, Krugman (1994) cautions not to place too much emphasis on the distribution of income in any given year. This exercise may be misleading, given the issue of income mobility. As people's employment and positions change over time, so does their income. Thus, families or individuals can move up and down in the income ranking. It is known that economic welfare is more dependent on average income earned over time than on the level of income in any given year. If the distribution of income is separated into quintiles, as it often is, income mobility would see some people moving between quintiles over time. However, even with the considerable amount of income mobility in the United States, it is not enough to make the

distribution of income irrelevant. The recognition of income mobility is important to assessing changes in the income distribution over time (Krugman, 1994).

2.4.2 Poverty

Measures of poverty are increasingly being used to help characterize the economic sustainability of an area. The most popular way to capture poverty in a single measure is the poverty rate. This measures the number of people with poverty status relative to the overall population of the area. The poverty rate reflects the distribution of income; thus it can complement measures of income distribution. Together, these two equity measures produce a good indication of economic distress (Stewart, Schuster, and McGinnis, 1996). The use of poverty rates as a sustainability indicator can be found in Stewart *et al* (1996), Force and Machlis (1997) and others.

The poverty rate is sometimes defined in a slightly different manner. For example, in Beckley's (2000) study of Canadian communities, the poverty rate was represented by the percentage of families below the poverty line. Beckley (2000) also reminds the readers that the placement of the poverty line differs according to location. Major urban centres may have higher costs of living, so the cut-off for low income may be elevated relative to smaller centres or rural areas.

In a study of counties in Montana, Haynes and Mohomed (1999) used the poverty line as a basis for their measure of the proportion of people living above the poverty line. The Ontario government chose to measure poverty as the proportion of Ontario children that live in poverty. Targeting child poverty is an attempt to build a promising future for youth who may have difficulties achieving their potential while living in poverty (Ontario Round Table on Environment and Economy, 1995).

The poverty rate is not the only way to measure poverty in terms of economic sustainability. Although the use of the poverty rate is supported by Berck, Costello, Fortmann, and Hoffman (2000), they were unable to obtain the rate on a monthly basis for their study in California. Therefore, as indicators of state and county level poverty, they chose to use poverty program participation levels. One such program was the Aid to Families with Dependent Children - Unemployed Parent Program (AFDC-UP). In this study about changes in employment demand, Berck *et al* (2000) believed that the AFDC-UP measure was superior to the poverty rate. By definition, the AFDC-UP is available to previously employed adults. Thus, participation in the program reflects the proportion of households whose well-being is most affected by cyclical economic trends. Berck *et al* (2000) also examined participation in a similar poverty program – the Aid to Families with Dependent Children Family Group (AFDC-FG). This program assisted children from single parent households. Participation in the Food Stamps program was also monitored. However, this poverty program was available to any low income households, regardless of family structure or employment history. Berck *et al* (2000) note that relationships (positive or negative) between unemployment, employment levels, and poverty exist at different scales. This study in Berck *et al* (2000) is one example of how poverty measures are useful when using economic models. Hence, a measure of poverty is included in this thesis. Consequently, this enabled the examination of the effect forest dependence and other community level indicators have on the poverty variable.

At the county level, Berck *et al* (2000) found that there was mixed evidence that timber employment decreases caused increases in Food Stamp program participation. As well, there was very little evidence that timber employment decreases were related to

increases in either ADFC-FG or AFDC-UP program participation in the short or long run (Berck *et al*, 2000). The incorporation of poverty measures into models of economic sustainability allows for the characterization of these relationships and for the prediction of impacts of employment changes on poverty.

When measuring sustainability on a global scale, Hammond (2000) reports two measures commonly used to determine poverty: the incidence of extreme poverty and the poverty gap ratio. The incidence of extreme poverty is a measure of the proportion of the population living on less than $1 / day. The poverty gap refers to the total shortfall of income from the poverty line, of all of the poor in the area. The poverty gap ratio is this calculation expressed as a per person percentage (Takayama, 1979).

2.5 Resilience Measures

Another group of indicators that help characterize sustainability is one measuring resilience[5]. Resilience refers to the degree that the economic system is sensitive to shocks (prices, demands, etc). Economic resilience consists of measures of employment and income diversity among economic sectors (Horne and Haynes, 1999). The most common resilience measures are the unemployment rate and different measures characterizing employment, and employment diversity. The unemployment rate is the proportion of people looking for work compared to the total labour force (Stewart *et al*, 1996). Employment diversity refers to balanced employment across industry sectors (Ashton and Pickens, 1995).

[5] Although resilience is a term originally used in biology circles, it has become widely used in relation to economic and social concerns. For the purposes of this study, resilience is interpreted in economic terms.

2.5.1 Unemployment Rate

The unemployment rate is a popular indicator used to measure economic sustainability as it can be used at any scale. As a performance indicator, it helps to determine how resilient the economy is to changes in some or all of its sectors. Stewart *et al* (1996), Ashton and Pickens (1995), Force and Machlis (1997), and others have used the unemployment rate to help quantify economic change. While economic sustainability is a multi-faceted concept, the unemployment rate can be examined in relation to other indicators to characterize the sustainability of an area. Hence, the unemployment rate at the CSD level is an important economic sustainability indicator examined in this thesis. Its relationship to other community level indicators, such as the incidence of poverty is useful in measuring sustainability. The interaction between equity and resilience measures is also seen in Berck *et al* (2000). These authors report that substantial literature has found positive relationships between unemployment and both poverty program participation and poverty rates at the state and national levels. Furthermore, in Gustavson *et al* (1999), multi-variate correlation studies were used to determine the relationships between various sustainability indicators. While these various linkages are important to understanding economic sustainability overall, the unemployment rate fares well on its own as a single measure of economic resilience. However, when using unemployment as an economic sustainability indicator, it is important to recognize some of the disadvantages as well. Due to the nature of its calculation, the unemployment rate will not include involuntary part-time workers, underemployed workers, or discouraged individuals who are no longer in the labour force. In addition, when examining economic sustainability at the community level, the unemployment rate may disguise economic

distress if previously unemployed workers have moved elsewhere to find work (Stewart *et al*, 1996). Unemployment can be reported monthly, but some authors choose to report this measure as an annual average to reduce seasonal effects.

2.5.2 Employment

The inclusion of any measure of employment in sustainability assessments is meant to complement other resilience measures in determining the response to economic changes. For example, the employment rate helps to determine what proportion of people have an increased ability to improve their living standards and meet their needs. Hillier (2000) used the employment rate (instead of the unemployment rate) as a sustainability indicator for the United Kingdom. This measure is reported as the percentage of workers relative to the total population of working age. This resilience measure also gives the government (at any level) an indication of where assistance could be useful. Public policy that increases employment opportunities is an important step to improving social exclusion and poverty, as well as decreasing dependence on welfare (Hillier, 2000).

Many authors use the overall employment, either alone or in conjunction with other variables, to capture an area's employment picture. Note that this employment measure is based on the economy as a whole, rather than the level of employment in a particular sector. Haynes and Mohomed (1996) used the employment rate and the female labour force participation rate as two indicators of county well-being in Montana. The use of these indicators can be explained by the fact that trends are easy to report due to their sensitivity to change and regular reporting periods (Beckley, 2000). In Beckley's (2000) study of nine Canadian communities, indicators were chosen that included overall

employment, labour force participation, the percentage of people with full & part-time employment, and the gendered divisions of labour within local markets.

Some researchers choose to use a slightly different employment measure by focusing on employment in a particular sector. Ashton and Pickens (1995) measured rural towns' dependence on USDA Forest Service programs. These authors chose resource use employment (RUE), and direct Forest Service employment as indicators. In attempting to model sustainable development indicators in the Fraser River Basin, BC, Gustavson *et al* (1999) included measures of the total employed labour force and the proportion of those employed in resource industries. Force and Machlis (1997) also chose employment-type indicators to assess socioeconomic conditions in the Upper Columbia River Basin. These authors used resource-related employment, women in the labour force, employment terms, work days (to capture seasonal employment), and the proportion of the labour force working in professional employment. Hardy Stevenson and Associates (1996) used the percentage of seasonal jobs, employment in the forest products industry and in other basic industries, employment in non-basic industries, and the changes in labour mobility as resilience measures. The firm tried to capture the impact of changes in timber harvest in Ontario (Hardy Stevenson and Associates, 1996). Furthermore, a study by Berck *et al* (2000) attempted to determine the impact decreased forestry employment had on the communities in the area. These authors used timber and non-timber employment to differentiate changes in sector composition. However, due to data constraints, timber employment only included employment in wood products and lumber industries. Berck *et al* (2000) also used total monthly state employment as a proxy for output of goods and services. They felt that the inclusion of this indicator was

important due to its integral role in determining labour demand at the state and county levels.

In many of the studies above, employment in a certain sector, such as the forest industry was used as an economic sustainability indicator. However, this may portray an inaccurate picture of employment overall. For example, in the forest sector, technical change will inevitably reduce the number of jobs available in this sector, but this does not necessarily translate into reduced employment in the overall economy. As Krugman (1998) states "...the effect of a productivity increase in a given industry on the number of jobs in that industry is very different from the effect of a productivity increase in the economy as a whole on the total number of jobs." It is agreed that a shift in the industrial structure of employment may occur as a result of technical change. However, this does not mean there has to be a net loss in the number of jobs. The explanation of this can be tied back to ever-increasing consumer demand. The United States has observed that productivity gains in one sector often lead to increased employment in other sectors. If these other sectors do not experience the same magnitude of technical change, employment here will increase to accommodate increased consumer demands for products and services. If production can increase by adding more workers, it will likely increase employment (Krugman, 1998). This evidence decreases the credibility of using sector-specific employment as a measure of economic sustainability. According to Krugman's (1998) theory, sector-specific employment would give the wrong signal to policy-makers.

2.5.3 Employment Diversity

Employment diversification plays a relatively large role in economic development, especially in smaller communities. As mentioned above, employment diversity refers to the distribution of employment across sectors. It can be stated with some certainty that "...counties with high employment diversity are better able to cope with changing economic conditions than less diverse counties over time." (Ashton and Pickens, 1995). Resilience can be measured according to the employment diversity index (Horne and Haynes, 1999). This index can be calculated using industrial employment or earnings. The Shannon-Weaver entropy index is commonly used as the vehicle for this calculation (Stewart *et al*, 1996). In a study of small, resource-dependent communities in the U.S., Ashton and Pickens (1995) used variables such as existing industries, the value of production and employment by each industry, and total employment and unemployment to partially calculate this index. Ashton and Pickens (1995) also identified the variables that quantified economic change, which may influence changes in employment diversity. Due to uncertainty as to what affects employment diversity, 44 causal variables were identified. These included changes in employment, unemployment, and changes in jobs by sector. The study concluded that diverse economies tended to have more constant levels of employment over time in each sector. They also found that even with stable resource related employment in a county, an absence of jobs in other sectors classified the economy as less diverse. This made these counties more vulnerable to changes in the economy. Ashton and Pickens (1995) also discovered that short-term economic change had little impact on the employment diversity unless the short-term

changes took place in smaller sectors of the economy. In terms of measuring sustainability, high employment diversity is sometimes thought to be indicative of higher resilience of the area in relation to economic shocks (Stewart *et al* 1996).

However, like many economic sustainability indicators, employment diversity is not without faults. For example, Attaran (1986) showed only a weak relationship between diverse economies and less unemployment. Overall, the study concluded that there was only very weak support for the claim that employment diversity leads to more resilient communities. However, as mentioned above, Attaran stresses that the industrial mix in the region is more crucial than the level of diversity. For example, in forest-dependent communities, industries that follow different business cycle trends as those driving the wood product industry should be encouraged more than industries whose trends are similar (Attaran, 1986). Diversity is important in relation to technical change. Technical change affects individual sectors differently, thus diversity would help to balance employment expansions or contractions among the different sectors.

2.6 Supplementary Indicators of Interest

While this chapter has focused on some economic sustainability indicators, it is worth noting that there are a number of indicators (ie. social) used to define sustainability that are related to economic indicators. However, these supplementary indicators are measured in different ways. For example, Beckley and Burkosky (1999) cited Kusel's attempt to create an aggregate measure of community capacity. This term refers to the measurement of community well-being as a whole and represents the potential for creating opportunities and improving well-being. In addition to measuring physical

capital, Kusel also included human and social capital. Human capital refers to the education, skills, and experiences of the citizens, while social capital is the willingness and abilities of the residents to collectively work towards community goals. Kusel combined subjective and objective assessments, making this measure of community capacity appealing for multidimensional sustainability monitoring (Beckley and Burkosky, 1999). Human capital was also used by Beckley (2000) in his study of community sustainability. However, Beckley admits that human capital is difficult to measure. For instance, Statistics Canada only reports educational attainment, which omits many other aspects of human capital such as on-the-job training (Beckley, 2000).

Most economic indicators that are used widely in studies of economic sustainability are derived from data sources such as the national census. Beckley *et al* (2002) label these indicators as 'profile' indicators; they are static in that they show a 'snapshot in time'. These authors advocate for these 'profile' indicators to be supplemented by the use of 'process' indicators that help researchers to understand the causal factors that affect an economy. Efforts are underway by Beckley *et al* (2002) to incorporate 'process' indicators such as sense of place, leadership, volunteerism, entrepreneurship, and social cohesion into an aggregate measure of community capacity. The authors hope that this measure will help prescribe what action must be taken to affect desirable change in a particular economy. This may be the case in the future, if further research into the interconnectedness of social, economic and ecological factors is undertaken. In turn, this could lead to the understanding of how to manipulate complex economies to produce the desired outcome.

In addition to community capacity, community well-being and community resilience are other constructs that Beckley *et al* (2002) believe are important for describing community sustainability. All three constructs involve the use of quantitative and qualitative assessment criteria. Preliminary results for some of the community capacity components strongly support the theory that both quantitative ('profile') and qualitative ('process') indicators are required to fully describe the economic and social dimensions of an economy (Beckley *et al*, 2002). For an extended description of the original ecosystem work that prompted the inclusion of community capacity, well-being and resilience constructs in the assessment of sustainability in resource-dependent communities, see the work of Kusel (1996).

There are also other empirical studies documenting the use of social indicators. In measuring socioeconomic well-being in Montana counties, Haynes and Mohomed (1999) included a variety of social sustainability indicators. Even though both social and economic indicators are used to measure sustainability, economic well-being and social well-being do not always move in tandem. For example, the Index of Social Health in the United States declined steadily from 1973-1995, yet GDP grew each year in this time period (Haynes and Mohomed, 1999).

A study by Force and Machlis (1997) compiled a list of social indicators to use in an assessment of ecosystem management in the Upper Columbia River Basin. While a few resilience and equity indicators were included, a large majority of indicators were social indicators.

Aside from supplementary indicators of interest in relation to economic sustainability, one last measure of economic progress is worth noting. The Genuine

Progress Indicator (GPI) is suggested as a measure of progress towards economic sustainability. The idea behind the GPI suggests that the conventional GDP measure should be augmented with various social and environmental costs and benefits to give a more holistic value of the economy. The GPI includes 20 categories that traditional measures of GDP ignore. These categories include things such as loss of leisure, environmental degradation, crime, and the value of the household economy. However, it is important to note that the 20 categories of the GPI are subjective in nature. Even though valuation of these added costs is varied and sometimes crude, advocates of the GPI feel that this valuation is better than excluding them altogether (Cobb, Halstead, and Rowe, 1995). The GPI is criticized by some for its composition as an aggregate index. There may be more problems using a composite index, rather than single economic sustainability indicators.

2.7 Conclusion

From the studies surveyed, there are a wide variety of indicators in the areas of income, equity and resilience that are used in attempts to quantify economic sustainability. However, in order to be useful, the indicator needs to be measurable (at a reasonable cost), normative and quantitative. A good indicator should also be able to forecast conditions into the future. In addition to all these criteria, the indicators chosen should be responsive and "forecastable" to changes in different management strategies and public policy, so they can reflect how economic changes affect sustainability concerns. This in turn, requires that the indicator reflect the theory behind the concepts of well-being or "economic welfare". All of these requirements support the use of the

Canadian national census as the primary data source for indicators used in this thesis. Its time series nature and spatial variability make it a sufficient basis for data.

A challenge for social researchers is to link sociological indicators with ecological and other variables. "To date such linkages have been weak, in part because there is so much statistical 'noise' going on in models that attempt to quantify community sustainability" (Beckley, 2000). It is important to keep in mind that social indicators themselves do not provide an indication as to why conditions may be changing. Social indicators are best used in the creation of a baseline description with which continued collection can identify trends that can be monitored (Force and Machlis, 1997). Combining social indicators with economic sustainability indicators only enhances their power. Unfortunately, the requirements for creating or attaining social indicators are usually outside the time, data, or monetary constraints that exist with most studies.

One of the key conclusions arising from this literature review is that economic sustainability should be evaluated for the economic unit (community, region, province, etc.) and not for a particular industrial sector (forestry, agriculture, etc.). Just as ecological sustainability indicators should take into account disturbances from various sectors (energy, forestry, etc.), so should economic indicators in order to assess overall economic condition. This concept, however, raises challenges for sustainable forest management. It is possible that one sector (the forestry sector for example) attempts to make management changes to improve economic sustainability but that these changes are counteracted by changes in other industrial sectors or by factors arising outside of the region. A single industry or sector should not be responsible for achieving sustainability when other agents are also influencing economic conditions. In order to truly evaluate

economic well being, however, this economy-wide perspective is important, and other sectoral measures may provide misleading information regarding economic sustainability.

Another challenge in the use of indicators will be the availability of suitable information with which to calculate or describe the indicator of interest. For example, indexes such as augmented income measures require information on non-market values. To address local or regional levels of sustainability, data would be required at the local or regional level. These information requirements rarely, if ever, are met. This illustrates the need to allocate sufficient financial and labour resources to generate the necessary information and to continue to generate this information to allow examination of temporal trends. This lack of information may be one of the reasons why so few regional studies of economic sustainability exist.

On the other hand, there are existing databases in Canada that meet some of the requirements for economic sustainability indicators. For example, as seen in this study, the national census is one source of information at a disaggregate level that with some reorganization of the information, proves useful in understanding some of the economic dimensions of sustainability. Since the census is a recurring data collection exercise, it meets some of the requirements for generating trends of indicators (such as the ability of indicators to be predicted or forecasted). This database is particularly useful in generating indicators relating to inequality (e.g. income distribution). Much of the census information, however, is not available at the individual level, and adjustments had to be made to generate useable information. Therefore, it is evident that tradeoffs exist between data accessibility and the usefulness of the indicators or measures that result

from using inadequate data. For example, data and time constraints did not permit the inclusion of augmented national/regional income measures in this study. Similarly, the indicators in the fourth group that often supplement economic sustainability indicators in studies of sustainability have also been excluded. This group usually includes social indicators like community capacity and community resilience. Instead, indicators in the areas of income, equity and resilience at the community level with the national census as a primary data source were chosen as the areas of interest for the measurement of sustainability indicators.

Once a database was constructed from census data and other sources, it contained a variety of economic sustainability indicators at the CSD level for 4202 CSDs across Canada. This database was used to answer three central research questions: (1) How does forest dependence in a CSD affect other variables such as incidence of poverty, income inequality, the unemployment rate, and median household income? (2) Is there anything unusual about how forest dependence affects other indicators? (3) How do other variables such as economic diversity, trade exposure, and aggregate demand affect indicators at the CSD level? Basic boxplots and graphs describe the data in the constructed database, while correlation analysis provides a preliminary look at the interaction of various indicators. Examples of other empirical studies serve as a guiding tool in specifying empirical models for the examination of this study's database. Random effects panel regressions were used to estimate these models. This approach allows for the definition of the relationships that exist between pairs of economic sustainability indicators while holding the other variables in the model constant. Thus, causation can be established, which is especially useful in determining the impact that forest

dependence has on various community level indicators. Therefore, the regressions may help to fully define relationships to answer the study's central research questions.

3 METHODOLOGY

This section begins with a discussion of the Canadian census and other data sources; it describes the data extracted for this research as well as the manipulations used to create a standardized dataset across three census years. This section also details the forest dependence calculations and methods used to derive other indicators included in the dataset.

3.1 Canadian Census

The database created for this study used the Canadian census as its foundation. Extracts were performed from the 1986, 1991, and 1996 Canadian censuses to obtain the desired variables (Statistics Canada 1986, 1991, 1996). For purposes of this study, the phrase 'each census year' will pertain to the years examined here: 1986, 1991, and 1996. Reasons for the exclusion of 1981 from this study are given in Point 1 in Appendix A. All extracts were obtained at the Census Subdivision (CSD) (municipality) level of geography. A complete definition of a CSD can be found in Point 2 of Appendix A. Two separate extracts were performed for each year; one from Profile 2A, whose data are gathered from a 100% sample of Canadians, and one from Profile 2B, whose data pertain to a 20% sample of Canadians. To obtain a single variable list for each year, the data from the two profiles were merged into one. When aggregating the two 1991 profiles, it was discovered that some CSDs were not common to both profiles. To create a complete dataset for 1991, all of the CSDs had to match for the entire list of variables. Thus, the missing CSDs (21 in all) were completely removed from the 1991 dataset. A list of these

CSDs as well as further description of the two profiles of data can be found in Appendix A under Point 3. Due to the time series nature of the analysis, these CSDs were removed from the 1986 and 1996 datasets as well to avoid missing data points for these CSDs.

The data in each of the three years then had to be standardized to allow for comparisons across time. Therefore, the variables from each census were matched across the three years. The 1996 Census Dictionary clarified terminology and assisted in this matching process (Statistics Canada, 1999). However, for the variables pertaining to employment by industry, the industry categories for 1986 did not match those in 1991 and 1996. The 1996 Census Dictionary (1999) stated that the industry categories in all three years were based on the 1980 Standard Industrial Classification (SIC) system and thus, should have been directly comparable. A search within the Statistics Canada Data Library Information series produced a table of 1986 industry data in the same 1980 SIC format as the 1991 and 1996 industry tables (Statistics Canada, 1986). This table was inserted into the 1986 dataset to replace the original table from the census database.

There have been changes to CSD boundaries, codes, and names across the 10 year span. Due to the complex nature of the charts pertaining to these changes, it was determined that the CSD changes would not be applied to the data until a final dataset was complete.

The last thing done to standardize the census extracts was to convert the monetary variables into constant dollars using the Consumer Price Index (CPI). This was done using 1992 as the base year. The three monetary variables in each dataset were average household income, median household income and the standard error of average household income. To ensure a more accurate analysis, the monetary variables for CSDs

in each province were adjusted by their respective provincial CPI numbers (Statistics Canada, 2001). A table of the provincial CPIs for each year can be found in Point 4 of Appendix A.

3.2 Generated Variables

Although the extracted census variables are interesting economic indicators in and of themselves, some of these variables were modified to produce new variables that may help examine economic sustainability.

3.2.1 Gini Coefficients

The household income classes from the census were used as a basis for calculating Gini coefficients for each CSD in each census year. This index of inequality provides a simplified look at the distribution of income in each CSD. A review of the literature revealed that many Gini coefficients were calculated with individual incomes. Due to the nature of the census variables, this was not possible. Hence, household income classes are the basis of Gini coefficient calculation in this study. It was also noted that the number of household income classes in each census were different. However, neither the nature (household income), nor the number of income classes, seem to compromise the quality of this variable. First, in calculating the Gini coefficient, Chevan and Stokes (2000) chose family income data over individual incomes defending their choice that a household's resources most directly affect an individual's lifestyle. Second, Chevan and Stokes (2000) and Lerman and Yitzhaki (1989) both concluded that very little of the variance in the Gini coefficient across time could be attributed to the different number of income class categories. However, when interpreting the Gini

coefficient, two things must be kept in mind. By calculating the Gini coefficient from household income classes, the coefficient may underestimate the level of income inequality in a CSD as the income of unrelated individuals is omitted. Also, due to the fact that the household income classes are formed from a 20% sample of the CSD, cross-sectional estimates such as the Gini coefficient are based on the representative sample (Chevan and Stokes, 2000). For the present study, the calculation of Gini coefficients based on household income classes was performed by modifying the method of calculation used by Yao (1999). Hence, this study produced a derived Gini coefficient for each CSD in each census year.

3.2.2 Forest Dependence

One of the main interests of this study was to examine economic sustainability indicators in communities (CSDs) which can be deemed forest dependent. The economic base theory (EBT) of regional economic growth provides the foundation for calculating a measure of forest dependence for each CSD in each census year. EBT states that a region's economy consists of a basic sector (export industries) which characterizes all local economic activity that is exogenously determined, and a non-basic sector (all other local economic activity) (Korber, 1997). Non-basic activity is dependent on the basic sector, so a region's economic growth is strongly determined by activity in the basic sector. Increases in basic sector activity cause an inflow of income into the region which creates a multiplier effect in the non-basic sector as this money is spent and re-spent in the region's economy (Pleeter, 1980; Mayo and Flynn, 1989; Korber, 1997). However, regional economic growth is not *solely* determined by exogenous demand. As population and economic activity increase in a community, internal factors such as labour

productivity, entrepreneurship, and capital play larger roles in determining economic growth (Blair, 1991). Thus, EBT is most appropriate when applied to studies of small communities, such as CSDs. By measuring the amount of basic activity in a CSD, EBT provides a theoretically solid framework in determining a CSD's dependence on external income in any industry. Thus, this theory can be used to estimate a measure of forest dependence.

Forest industry dependence is defined as the proportion of activity in the forest sector that contributes to the CSDs total basic economic activity (Korber, 1997). Accurate measurement of a CSD's basic activity is the chief difficulty in applying EBT to any community. Although the location quotient is sometimes criticized for its restrictive assumptions (discussed below), it is commonly used to measure basic activity due to its low costs and for the ability to use publicly available data (Blackley, 1992). Alternatives to estimating basic sector activity are discussed in Isserman (1980), Pleeter (1980), and Richardson (1985). The location quotient formula offers several possible measurement units, including employment, income, sales, and value added (Fletcher, 1991).

For this study, employment income was used[6]. Employment income for an industry can be defined as: the number of people employed in the industry, multiplied by the average income for the industry. The source for the employment numbers by industry was the Canadian census (Statistics Canada 1986, 1991, 1996). Although employment data implicitly assume all jobs are the same type (full-time, part-time, seasonal, temporary), employment income data at least differentiate the jobs in terms of

[6] Preliminary work by Korber (1997) has shown that including transfer income as a non-employed, income earning sector can change forest dependence results. In this context, a community with high transfers is actually less forest dependent, and has less income than if the community's forest dependence was measured using the methodology in this study. Thus, forest dependence in this study may be overstated.

remuneration (discrete average incomes) (Korber, 1997). Additional problems with using census employment numbers and other census data are discussed in Point 5 in Appendix A.

In this case, the location quotient can be interpreted as a ratio of a CSD's share of employment income in industry *i* to a benchmark (province's) share of employment income in the same industry. The formula, from Fletcher (1991) which measures basic employment income, is as follows:

$$LQ_j^i = \left[\frac{(E_j^i / E_j^T)}{(E_p^i / E_p^T)} \right] \qquad [2]$$

where LQ_j^i = CSD's location quotient for industry i, E_j^i = CSD's total employment income for industry i, E_j^T = CSD's total employment income over all industries, E_p^i = provincial employment income for industry i, and E_p^T = total provincial employment income over all industries. However, E_p^i is replaced with this equation:

$$E_p^{i*} = \left[\frac{(T_n^i - X_n^i + M_n^i)}{T_n^i} \right] E_p^i \qquad [3]$$

where E_p^{i*} = weighted share of employment income needed for provincial self-sufficiency in a province where there are no net exports, T_n^i = total national output from industry i, X_n^i = national exports from industry i, M_n^i = national imports from industry i, and E_p^i = total provincial employment income for industry i.

The benchmark (province) represents the level of employment income that is necessary to provide for domestic consumption. If the location quotient is greater than one for industry *i*, this means that the industry is producing more than is necessary (i.e.

more than the benchmark) for local consumption in the CSD. It is assumed that the excess production is intended for exogenous demand, which constitutes basic activity in that industry. Implicit in this calculation is the assumption that each industry has equal average productivity and consumption in both the CSD (region) and the province (benchmark) (Isserman, 1980). Thus, by using the province as a benchmark, the likelihood that average productivity and consumption would differ greatly from the benchmark levels in any given industry would be small (Korber, 1997).

Another assumption implicit in using the location quotient is that neither the CSD nor the province are net exporters or net importers for any industry (Isserman, 1980; Richardson, 1985). However, since exports and imports are seen at both levels (which invalidates this assumption), some modifications are necessary. The distorting effects of imports and exports in the location quotient formula at the CSD level can be alleviated somewhat by using the most disaggregated industry data possible (i.e. the most detailed 3 or 4 digit SIC codes) (Pleeter, 1980; Richardson, 1985). This is a drawback in this study. Since the accuracy of location quotients increase with disaggregation, location quotients based on industry data at the division level should be interpreted with caution. A modification at the provincial level is seen in the modification to provincial employment income by industry in equation [3]. This is necessary to adjust for the fact that a province exports and imports to meet provincial consumption demands (Isserman, 1980). Thus, a province's share of employment income in each industry is weighted by the proportion of its output minus net exports to show the amount of output needed to meet domestic consumption.

Given a positive location quotient, the next step in the forest dependence calculation is:

$$X_j^i = \left[\frac{LQ_j^i - 1}{LQ_j^i}\right] E_j^i \qquad [4]$$

where X_j^i = proportion of employment income in industry *i* that is attributed to basic sector activity. Following this, the total base employment income for a CSD can be calculated as:

$$X_j^T = \Sigma X_j^i \qquad [5]$$

where X_j^T = total of all basic sector employment income. Finally, forest dependence is calculated using the following index:

$$\text{FDI (Forest Dependence Index)} = \frac{X_j^i}{X_j^T} \qquad [6]$$

where X_j^i = basic forest industry sector employment income (Fletcher, 1991).

Hence, the FDI is the proportion that the forestry sector contributes to a CSD's economic base. This forest dependence index is useful to categorize CSDs by the degree of forest dependence, whose basic forestry employment income is vulnerable to external market or policy shocks (Korber, 1997).

Although the Canadian census was the source for the employment data, the census profiles used in this study did not include the average income by industry variable. The source of the average income by industry variable for 1986 and 1991 was a custom tabulation from Statistics Canada (1995). This database contained different employment related variables for each CSD and province in Canada (in their respective years). Any

industry data from this source were presented according to 1970 SIC classification. However, the industry structure for the census employment data is presented according to 1980 SIC at the Division level (least detailed list of industries). A list of these 1980 SIC divisions can be found as Point 6 of Appendix A. Thus, a concordance file was necessary to transform the 1970 SIC data to the 1980 SIC format (Statistics Canada, 2000). After completing the concordance, most 1980 SIC industry categories from the custom tabulation contained more detailed industry sub-sectors. Each of the sub-sectors in an industry contained two categories of data relevant for this study: one for employment, the other for the sub-sector's average income. For industries that contained sub-sectors, the average incomes of the sub-sectors were weighted by their respective employment numbers to produce an overall average income for each industry. If a sub-sector was missing either an employment number or average income, the entire sub-sector was ignored; the industry's overall average income was calculated using the remaining sub-sectors' data.

In this database, some sub-sectors reported negative average incomes. These negative values were mostly confined to very small communities and are explained by the presence of self-employed individuals who may have incurred a loss in that year. The negative values were preserved in the overall average income calculation, but if the overall average income was a negative number, the number "1" was inserted in its place. This was to avoid error messages (from a negative number) in future calculations, yet it still portrayed the fact that the average income in that industry was *very* small. However, even though these sub-sectors reported an overall negative income, it is quite possible that this occurred from the self-employed individuals maximizing their small business

deductions. In this case, these people probably did have some positive income that is not captured in the overall sub-sector average income. Thus, due to the nature of the forest dependence index calculations, when a negative average income is reported, it lowers the overall community income and probably slightly overstates the degree of forest dependence in the CSD. Fortunately, this problem of negative income numbers was not very prevalent, so this issue did not significantly affect the entire database.

There were instances where an industry's overall weighted average income was zero, due to the fact that each of that industry's sub-sectors was missing either employment or average income data. In these cases, that industry's average income for that particular CSD was replaced with the CSD's respective provincial industry average income.

The average incomes for Divisions K (Finance and Insurance Industries) and L (Real Estate Operator and Insurance Agent Industries) within each CSD for 1986 and 1991 are identical. Since the original data from this database existed in 1970 SIC form, Divisions K and L were one category (Finance, Insurance, and Real Estate). According to the 1980 SIC, they were split into the current two categories. Since it was impossible to divide the data knowingly, an overall average income (weighted by the respective employment numbers) was calculated (for each industry in each CSD) for the one 1970 division and applied to both of the 1980 divisions.

The 1986 and 1991 average incomes by industry are not perfect, as they were weighted by the employment numbers from that source, not the census employment numbers used later in this study. These two sources referenced the same CSDs in the same years, but the employment numbers between them differed slightly. Due to the fact

that there are various census tabulations for the same geographic areas and variables, minor differences are expected (Statistics Canada, 1999).

Upon comparing the 1986 and 1991 list of CSDs and their average incomes, it was discovered that 1991 was missing information for 787 CSDs that were in the 1986 dataset. The reason for this lay in the Statistics Canada rules for data suppression in 1991. Hence, all but three CSDs in the 787 CSDs missing information had populations below 515 people. The possible rules that accounted for the omission of information for the 787 CSDs are documented in Point 7 of Appendix A. To avoid deleting these 787 CSDs from every census year, a viable estimate of average incomes for each industry in each of the 787 CSDs had to be created. This was achieved with the help of the remaining CSDs that had reported average incomes. Using provincial maps that displayed the locations of all Canadian CSDs, the average incomes for each industry in each of the missing 787 CSDs were determined by taking the closest true values of the average incomes in neighbouring CSDs (Statistics Canada, 1992). Thus, if the closest CSD had two industries with provincial averages (from having an original zero value), the next closest CSD was searched for an actual value in these two industries that would complete the list of average incomes for the missing CSD. By estimating the average incomes for these 787 CSDs, the list of CSDs for the 1986 and 1991 average incomes now matched.

The data for average income by industry for 1996 was taken from a separate custom tabulation (Statistics Canada, 1999). The data were presented by the 1980 SIC, so Divisions K and L have their own respective average incomes by industry in each CSD. This year of average incomes was treated the same as 1986 and 1991, in the fact

that any negative average incomes were changed to a "1", and any zero values were replaced with the proper provincial industry average income.

Once the average incomes were derived for each industry in each CSD in each census year, they were multiplied by the census employment by industry numbers. This gave employment income values by industry for each CSD (the first variable needed in the Location Quotient formula). Even though Divisions K and L had identical derived average incomes for 1986 and 1991, they had discrete employment numbers from the Canadian census. Hence, these divisions remained separate in the forest dependency calculations. The multiplication of the derived average incomes to the census employment numbers also required that the CSD lists for the two variables to be identical. Thus, the 21 CSDs that were missing from the initial census data aggregation had to be removed from the average income files for each year. Once this was complete, the average income and census employment files for 1986 and 1991 matched, but 1996 required some modifications. The list of CSDs for the 1996 average incomes and census employment numbers differed by only 15 CSDs. Since 13 of the 15 CSDs had populations below 670, the missing CSDs could be due to data suppression. The average incomes by industry for these 15 communities were treated the same as zero average income values for an industry in 1986; they were replaced with provincial averages. Once these average incomes in each CSD were given the same values as their respective provincial average incomes by industry, the 1996 list of CSDs matched between the average income and employment files. Since the average income and employment files now had matching lists of CSDs for each year, they were multiplied to give the employment income values for each industry in each CSD for each census year.

In the Location Quotient formula, each CSD's employment income is compared to its respective province which serves as the benchmark. The provincial employment income variable was calculated in the same way as the CSD variables, as the required provincial data were resident on the both databases. As seen in equation [3], the provincial employment income in each industry must be replaced with a new formula, one that shows how the employment income value is modified by its provincial output, imports, and exports.

However, national output, imports, and exports are used. This is due to the fact that each province collects its own input-output data, so the content and presentation across provinces vary. Without a standardized collection process, the provincial numbers cannot be adequately compared[7]. To test the validity of using the national numbers, the correlation was studied between Location Quotient values using national numbers and Location Quotient values using regional numbers (found for just one year). Since the values were approximately 99% correlated, the inclusion of national numbers can be considered valid.

Although the national output values for each industry can be found in each year's Output Matrices, this was not the source used for 1986 and 1991. In 1998, Statistics Canada released a 1997 historical revision of the Canadian System of National Accounts (CSNA). It contained 32 years of revised data (1961-1992) from the Canadian Input-Output Accounts that completely superceded all previous national input-output account data for all of these years. This historical revision was undertaken for a number of reasons, including making the CSNA more internationally comparable, and enhancing its analytical usefulness. As such this historically revised document was used to reflect the

most accurate national output by industry for 1986 and 1991 (Statistics Canada, 1998). Since a similar historically revised document has yet to be published for 1996, the national output by industry was taken from the 1996 Output Matrix (Statistics Canada, 2001). All of the national output data were presented at the 1980 SIC Division level – the same level at which the census data are presented. However, national imports and exports by industry at this level are not publicized documents. The details surrounding this issue are discussed as Point 8 in Appendix A. Thus, this data had to be obtained by a custom tabulation (Statistics Canada, 2002).

The national output, imports, and exports by industry data were used to modify the original Location Quotient formula for each of the 18 industries. It must be noted that even though Division K and L were managed as discrete industries, the import/export data reported a single number for these two industries combined. Although one option would be to divide each import and export in half and apply the result to Divisions K and L, the import and export numbers were retained as given and the full formula modification was made to Division K, and no modifications were performed to Division L. The reason for this is that it is more likely that Division K (Finance and insurance industries) reports imports and exports than Division L (Real estate operator and insurance agent industries). Following through the rest of the calculations, equation [6] can be used to calculate a measure of dependence for any industry. Equation [4] yields basic employment income for each industry. Thus, to determine an area's dependence on a certain industry, the numerator in equation [6] will be the value obtained in equation [4] for the desired industry.

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[7] CSD-level export and import data are available, but only at a considerable cost.

In order to capture all forest related activity within the measure of forest dependence, all forestry associated industries or sub-sectors should be included in the final dependence calculation. With the original 1986 and 1991 industry data in terms of 1970 SIC, it allowed us to see the more detailed sub-sectors that exist within each industry. By its sub-sectors, and 1980 industry name, it is clear that Division C (Logging and Forestry Services) will be used in the dependence calculation. The sub-sectors in each industry were used to further examine every other industry for other forestry activity. The only other applicable industry was Division E (Manufacturing industries), which contained 3 major sub-sectors: Base Manufacturing Industries, Wood Industries, and Paper and Allied Industries. The Base Manufacturing Industry sub-sector includes manufacturing of almost all goods except forestry products. The manufacturing of forest products is contained in the Wood Industries and Paper and Allied Industries sub-sectors (Statistics Canada, 1995). Therefore, it was necessary to isolate the proportion of employment income that comes from Wood Industries and Paper and Allied Industries, which would then be multiplied by Division E's total forest dependence index. By retaining the data in 1970 SIC format, the raw data of employment numbers and average income for the Wood Industries and Paper and Allied Industries sub-sectors was used to calculate forestry related employment income in this division. The same data for Base Manufacturing Industries was used in conjunction with the other two sub-sectors to give an overall measure of Division E's employment income.

The proportion of forest activity in Division E ($DivEP_{FA}$) was then calculated as follows:

$$DivEP_{FA} = \frac{W_j + Pap_j}{\sum W_j + Pap_j + M_j} \qquad [7]$$

where W_j = CSD's employment income in Wood Industries, Pap_j = CSD's employment income in Paper and Allied Industries, and M_j = CSD's employment income in Base Manufacturing Industries. Thus, the final calculation to determine the amount of forest dependence in a CSD (Total FD) is:

$$\text{Total FD} = \text{Div C FD} + (\text{Div E FD} * \text{DivEP}_{FA}) \quad [8]$$

where Div C FD = forest dependence from Division C, and Div E FD = forest dependence from Division E[8].

This procedure was performed for every CSD on the 1986 and 1991 industry database, but the 787 CSDs that were missing from 1991 still posed a problem. These CSDs were small communities with suppressed data. Since no data was available to calculate the proportion of forest activity in Division E, the proportions were assumed to be zero for these 787 CSDs. Hence the forest dependence in these CSDs was based on the Division C dependence index only. Although this is conservative, one can be sure that the forest dependence index in these communities is not overestimated.

The same formulas for determining the proportion of forest activity in Division E were used for 1996, but the sources of all the industry data were different, which made a few data modifications necessary. The Statistics Canada (1999) file that was used for average incomes by industry in each CSD was combined with a new file, also a custom tabulation from Statistics Canada. This file was the related employment numbers for each industry in each CSD. Used together, the two files derived Division E total

[8] There may be other sub-sectors that include forestry-related activity. For example, independent log haulers in the Transportation division are often overlooked. Inadvertently excluding these types of sub-sectors may cause the measures of forest dependence calculated in this study to be understated. I thank W.A. White for bringing up this issue.

employment incomes for each CSD. Since neither of these files gave information by industry sub-sector, an additional data source had to be used. In a tabulation similar to the other two, Statistics Canada presented employment and average incomes in each industry's sub-sectors (Statistics Canada, 1999). Thus, equations [5] and [6] were derived. The same modifications that were needed to match the average income file to the census data were made to the proportion files. Also, the 15 missing CSDs in 1996 that had to be added in to the proportions to match the CSDs, were treated like the 787 CSDs in 1991. The proportion of forest activity in Division E was assumed to be zero. Thus, the forest dependence index in these 15 CSDs is entirely represented by activity (if any) in Division C. Due to some problems within the different data sources used, the proportions for 64 CSDs had to be estimated on the basis of employment in each of Division E sub-sectors, rather than employment income. Although this does not fully correspond to the rest of the data calculations, it was the best solution for this small group of CSDs. The final forest dependence indices for each CSD were inserted as a new variable into each year of the database.

3.2.3 Trade Exposure

Trade exposure also likely affects the economic activity of a CSD. If a CSD's trade exposure is substantial for exports or imports, it means that the community is vulnerable to outside markets. The exposure of a CSD to international trade can be measured as the sum product of the trade exposure of its industries and the CSD's employment income of its industries (Osberg and Cyrus, 2000). Although trade exposure can be calculated strictly by employment, the employment income method was chosen here to be consistent with the other variable calculations. A popular measure of trade

exposure is one that is derived from combining exports and imports. The equation used here (from Osberg (2000)) is as follows:

$$\text{Trade Exposure (of exp and imp)} = \sum \left[\frac{E_j^i}{E_j^T} * \frac{(X_n^i + M_n^i)}{T_n^i} \right] \qquad [9]$$

where E_j^i = CSD's employment income in industry i, E_j^T = CSD's total employment income over all industries, X_n^i = national level exports in industry i, M_n^i = national level imports in industry i, and T_n^i = national level output in industry i. The impacts that exports alone and imports alone have upon a CSD are also worth examining. With the appropriate modifications, equation [9] serves as a way to derive these two variables as well. These three trade exposure variables were added to the dataset.

3.2.4 Diversity

In keeping with measuring a community's vulnerability, a diversity variable was also derived. Again, this variable may be derived strictly in terms of employment, or in terms of employment income. To see the sensitivity between the two methods, diversity was derived using both the employment and employment income methods. The diversity variable is calculated by using a variation of the Shannon entropy index. The employment income method of deriving diversity of a CSD is as follows:

$$D(P_1, P_2, \ldots, P_n) = - \sum_{i=1}^{n} [P_i * \ln P_i] \qquad [10]$$

where n = number of industries, and P_i = employment income in industry i. The employment method uses the same formula with the appropriate modifications (Ashton and Pickens, 1995). Using the 1980 SIC "S" level of categorization, the number of industries in all cases here is 18. Thus, the maximum level of diversity a CSD can obtain is ln(18) = 2.890. Every derived diversity value is compared to this maximum value to

determine the diversity of a CSD. A diversity value of 0 can only be obtained if all of a CSD's employment income is contained in one sector (Attaran and Zwick, 1989).

3.3 CSD Boundary and Other Changes

Once a final dataset had been constructed, the CSDs had to be made compatible across all three years. Most of the discrepancies existed from various name, type, code, and boundary revisions that had occurred from 1986 to 1996. The extent of the changes that were applied to the full dataset, as well as their sources are described in detail in Point 9 of Appendix A.

After all plausible changes, the entire database was filtered to exclude any CSD that did not have all three census years of data. Following this, the entire dataset contained 5051 CSDs in each year. For reference, the total number of CSDs for the 1986, 1991, and 1996 censuses were 6009, 6006, and 5984 respectively (Statistics Canada 1987, 1999). Next the dataset was further cleaned. Any CSD that was missing a value for the Forest Dependency variable for any year was removed from the dataset. Due to the nature of the forest dependency calculation (see equation 2) this meant that the CSD was also missing raw employment data, thus missing values for the diversity and trade exposure variable calculations. This process resulted in the deletion of 111 CSDs. The same procedure was repeated for the Gini coefficient. Any CSD missing a value for a Gini coefficient in any year was also missing important income data such as incidence of low income for all groups, median household income, average household income, and the household distribution among income classes. This income data were suppressed in the census if the CSD had a population below 250 people. This essentially resulted in the

deletion of 737 CSDs, most of which had populations below 250. The missing data in all cases were key variables for this study, thus the deleted CSDs would not have added to the results at all. Also, although some CSDs were only missing the key variables in one year only, there were still deleted as the temporal component of the study is crucial for the comparison of indicators over time. These two methods of deleting CSDs left 4202 CSDs in the final dataset. All CSDs have a population above 250 in any year, except three CSDs. However these three had all of the data for all 3 years, so they were retained in the dataset. A table showing the share of CSDs from each province (using the 1996 census) that comprises the final dataset is shown in Point 10 of Appendix A.

4 A DESCRIPTIVE ANALYSIS AND EXPLORATION OF THE INDICATORS[9]

In this chapter the indicator data are explored using descriptive statistics. The section begins with an examination of the distribution of the forest dependent CSDs (ie. Forest Dependence index > 0) across Canada, and continues to describe each indicator over the time series. In addition, the relationships between the indicators are examined using correlation analysis. This section concludes with an examination of forest dependent vs. non-forest dependent CSDs in Canada.

4.1 Forest Dependent CSDs

4.1.1 Frequencies – Forest Dependence

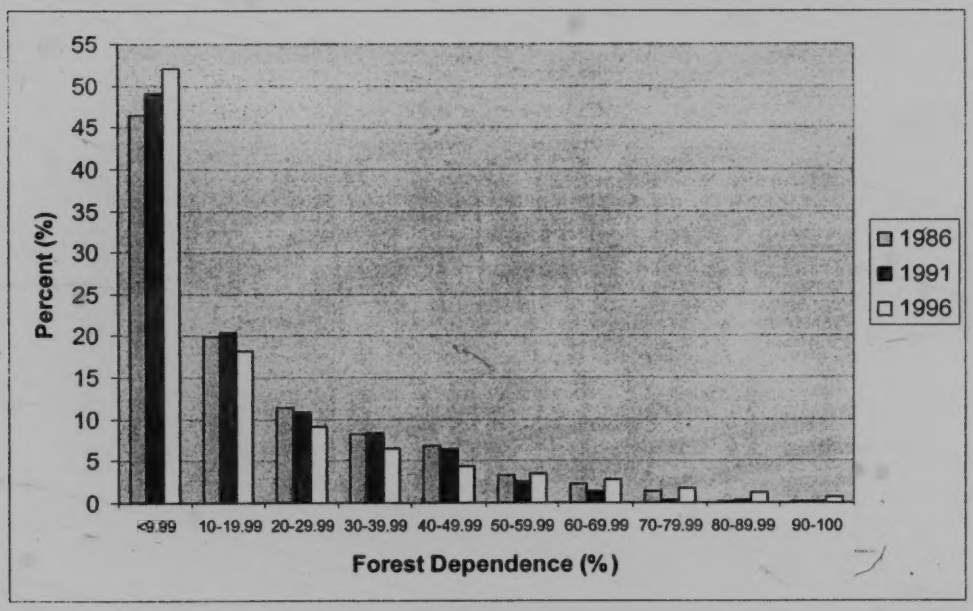
The proportion of forest dependent CSDs in each year is compared to non-forest dependent CSDs and the total number of CSDs in the dataset in Table 1. In each year, roughly half of all of the CSDs in Canada could be deemed 'forest dependent'. For purposes of general exploration of the data, a simple frequency distribution was constructed for all CSDs in Canada (in the dataset) by degree of forest dependence. Because of their large number (see Table 1), CSDs with zero forest dependence were excluded for this distribution. The resulting distribution of the percent dependent on forestry is shown in Figure 1.

[9] Chapters 3 and 4 have been published as a Sustainable Management Network Project Report (2002-9)

Table 1: Comparison of CSDs by Type to Total Number of CSDs from 1986-1996

	Number of Forest Dependent CSDs (% of the total for each year)[†]	Number of Non-Forest Dependent CSDs[Δ]	Total Number of CSDs
Year			
1986	2104 (50.1)	2098	4202
1991	2000 (47.6)	2202	4202
1996	2305 (54.9)	1897	4202
	[†] Forest Dependence Index > 0	[Δ] Forest Dependence Index = 0	

Figure 1: Degree of Forest Dependence among Forest Dependent CSDs



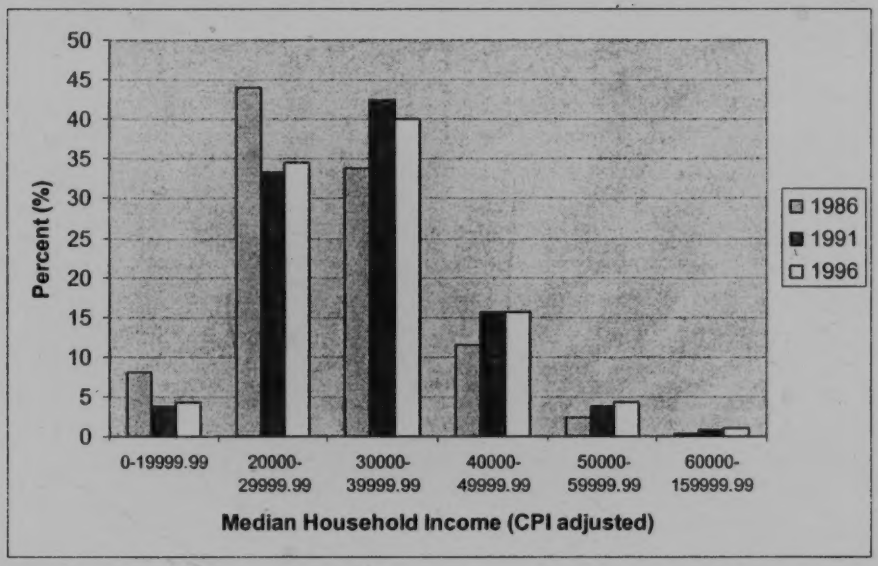
Over the period 1986-1996, there was an increase in the proportion of CSDs in the categories of high forest dependence (more than 50%) and low forest dependence (less than 10%). There was a reduction in the percentage of CSDs in the moderately forest dependent categories. Thus, over the time period some of the CSDs that were in the middle categories became either more or less forest dependent. For this group of forest dependent CSDs across Canada, various economic sustainability indicators in the

categories of income, equity and resilience over the period 1986-1996 and as a function of forest dependence level are examined.

4.1.2 Income

At the CSD level, median household income is reported in the Canadian census for 1986, 1991, and 1996. According to the census a household is "...a person or a group of persons who occupy a private dwelling." (Statistics Canada, 1999). The distribution of median household income among the forest dependent CSDs is shown in Figure 2.

Figure 2: Median Household Income Distribution among Forest Dependent CSDs



Over the period of 1986-1996, the number of households in the lowest categories of median income declined and the frequencies in the higher median household income categories increased. This shift in the distribution across the three periods suggests that the median household income increased among the forest dependent CSDs from 1986-1996.

A boxplot of median income against the degree of forest dependence for each year can help to clarify the relationship between these two variables. These boxplots are

shown in Figure 3[10]. The number of CSDs that exist within each forest dependence class is also specified along the 'x' axis. If the highest two classes in 1986 and 1991 are excluded (due to the small number of CSDs in those classes), it is seen that median household income was relatively stable over the 1986-1991 period. However, in 1996 not only did the number of communities in the highest three forest dependent classes increase markedly, there was also a rise in median household income in these classes. Both of these events can be at least partially explained by looking at the national forestry product price indexes where 1986=100. The average indexes for 1986, 1991, and 1996 in the lumber, sawmill and other products category were 99.99, 105.73, and 160.09 respectively. In the paper and other paper products category, the average indexes for 1986, 1991, and 1996 were 100.01, 109.88, and 141.74 respectively (Statistics Canada, 1997). Thus, between 1991 and 1996 there was a substantial increase in the forest products price indexes, most likely causing forestry activity (including employment and income in this sector) to increase. This suggests that a relationship might exist between the price indexes and median household income. The boxplots show that as CSDs became more forest dependent, they also experienced a rise in their median household income in 1996. Thus, there may be a positive relationship between forest dependence and median household income. However, the correlation analysis and empirical models must be used to verify this hypothesis.

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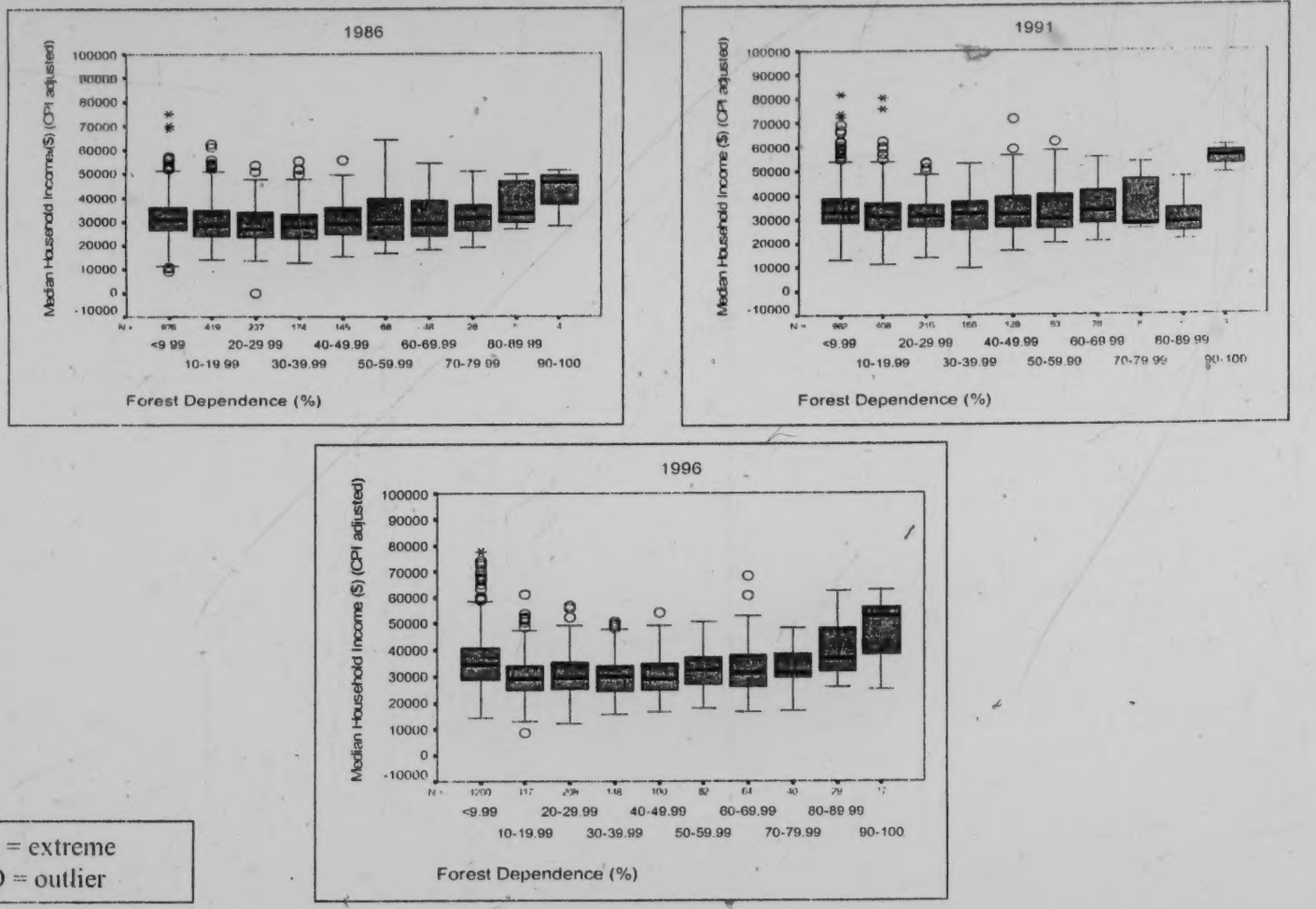
[10] The boxes represent the interquartile range which contains 50% of the values, while the center line is the median of the variable in that category. The 'whiskers' that extend past the box in either direction are lines to the highest and lowest values, excluding outliers. Observations within 1 ½ - 3 box lengths from the top or bottom are outliers, and values beyond three box lengths are called extreme values (Norusis, 2000).

Figure 3: Boxplots of Median Household Income by Degree of Forest Dependence among Forest Dependent CSDs



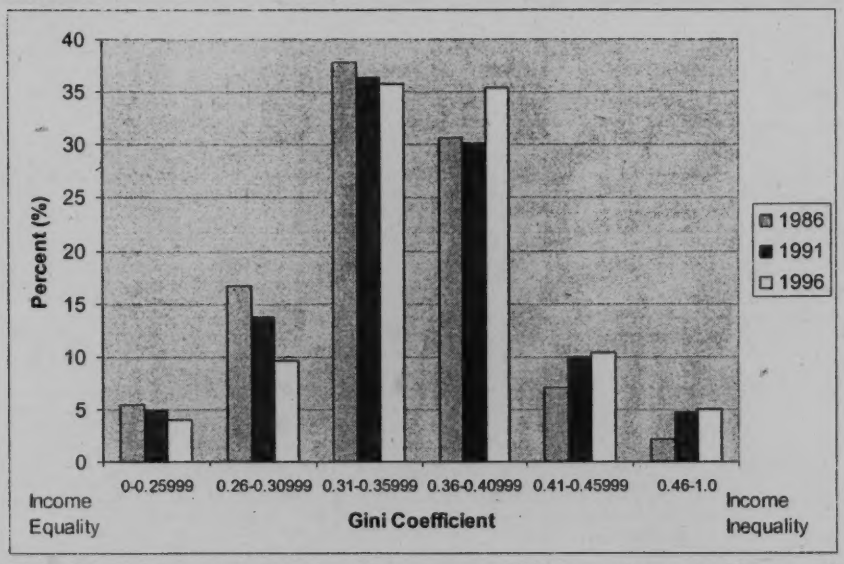
4.1.3 Equity Measures

The distribution of income and the number of families in low income situations is also of concern when examining the level of well-being in a community. These measures are explored below.

4.1.3.1 Gini Coefficient

The Gini coefficient is calculated from the distribution of households within a CSD among various income classes. The Gini coefficient measures the equality (or subsequent inequality) of the distribution of income in the CSD. A Gini of 0 reflects perfect income equality where every household earns the same proportion of the total income earned in the same CSD. A Gini of 1 reflects complete inequality where one household earns all of the total income earned in the CSD. The distribution of the Gini coefficient among the forest dependent CSDs in shown in Figure 4.

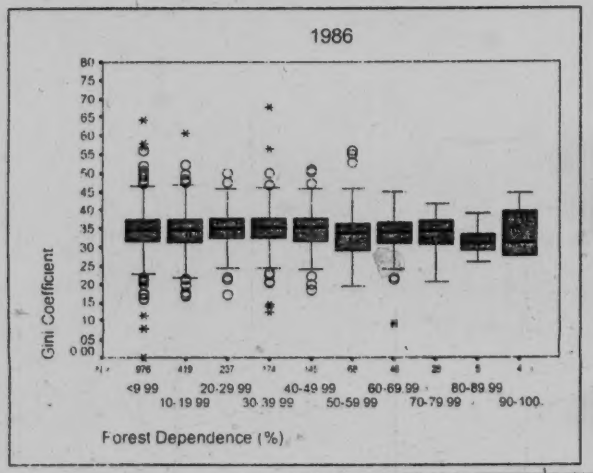
Figure 4: Frequency Distribution of the Gini Coefficient among Forest Dependent CSDs

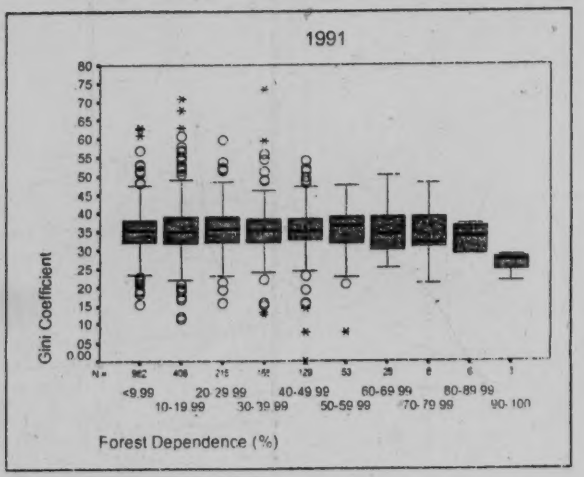


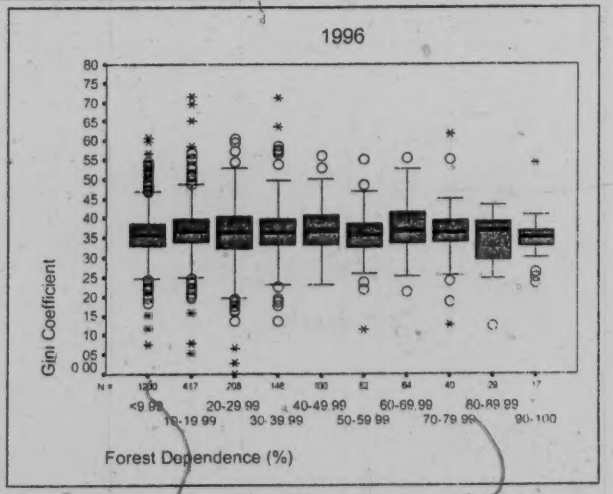
This distribution suggests that there was a shift towards greater income inequality over the period 1986-1996 for forest dependent CSDs in Canada.

The boxplots for Gini coefficient against forest dependence, shown in Figure 5, provide further explanation of the Gini coefficient in the various forest dependence classes. Again excluding the top two forest dependence classes for 1986 and 1991, the Gini coefficient remains relatively stable from 1986-1996 regardless of the degree of forest dependence in the CSD. Thus, the increases in income inequality in 1996 (as observed in the frequency distribution graph) were most likely spread across the forest dependence classes, as this result did not show up in the boxplots. The stability of the Gini coefficient across the forest dependence classes and through the time series suggest that the Gini coefficient values in a CSD are independent of forest dependence. This result will be explored by examining the degree and direction of their correlations in a later section. However, it must be noted that the stability of the Gini coefficient across the forest dependence classes does not mean that the Gini coefficient is stable over time within any given CSD. The distribution of Gini coefficients across CSDs is relatively stable, but this does not prevent individual CSDs moving between classes of forest dependence (reflecting changes in forest dependence) and within their forest dependence class (reflecting changes in income inequality).

Figure 5: Boxplots of the Gini Coefficient by Degree of Forest Dependence among Forest Dependent CSDs







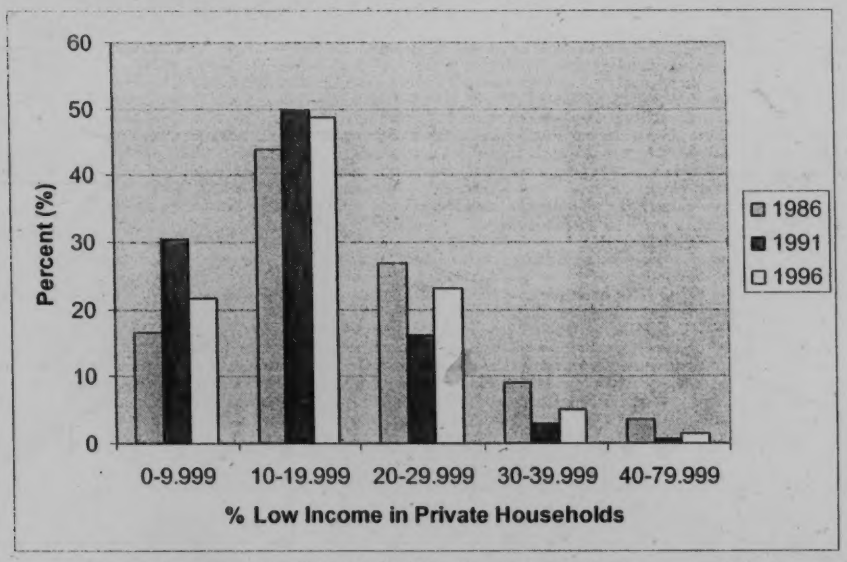
* = extreme
O = outlier

4.1.3.2 Incidence of Low Income Among People in Private Households

Although the measurements may vary, an indicator representing poverty is common in most studies of economic sustainability. One variable related to poverty provided by the Canadian Census is the incidence of low income for various groups of people such as economic families, unattached individuals, and people in private households. This indicator also helps to portray equity (or inequity) in an area since it can reflect the incidence of poverty in a CSD. For consistency with the other variables of interest, this statistic is reported only for private households. A private household is defined as "...a person or a group of persons (other than foreign residents) who occupy a private dwelling and do not have a usual place of residence elsewhere in Canada." (Statistics Canada, 1999). Also in the census, the incidence of low income among people in private households is the percentage of people living in private households below the low income cut-offs. In turn, the low income cut-offs (LICO) are determined by the proportion of expenditure required for food, shelter, and clothing (basic necessities).

An appealing characteristic of this poverty indicator is that the LICO's are set at income levels differentiated by household size and degree of urbanization, which are updated yearly by changes in the Consumer Price Index (Statistics Canada, 1999). This validates the use of this indicator as it doesn't apply a universal LICO to all households or all CSDs as some poverty indicators do. Thus, the incidence of low income among people in private households is the proportion of people in households that are classified as 'low income' (by their expenditure on basic necessities) due to their household size and the size of their CSD. The graph depicting this statistic for the forest dependent CSDs is shown in Figure 6.

Figure 6: Incidence of Low Income among People Living in Private Households among Forest Dependent CSDs

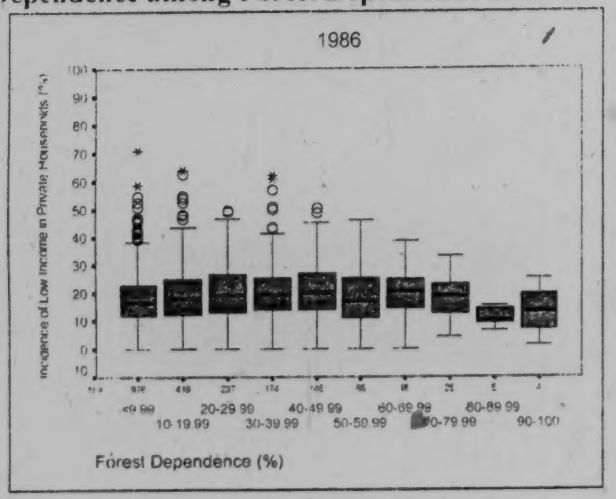


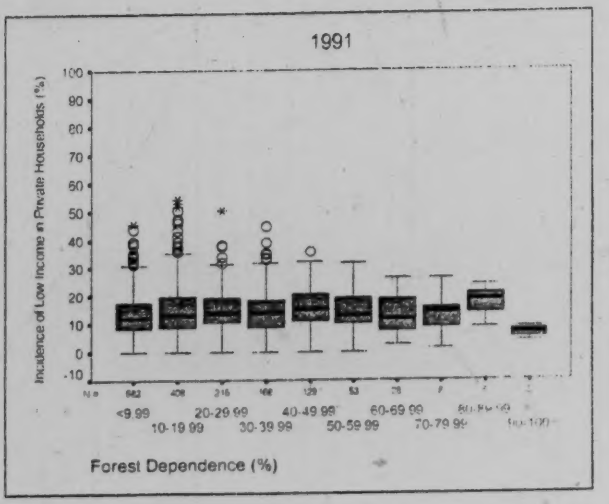
Over the period of 1986-1996, the distributions suggest that among forest dependent CSDs in Canada, there was a slight shift in the distribution of CSDs from the higher percentages of low income to the lower categories. This is most evident from 1986-1991, but in 1996, there was an upward shift in the distribution. This suggests that in forest dependent communities the incidence of low income for people living in private households increased.

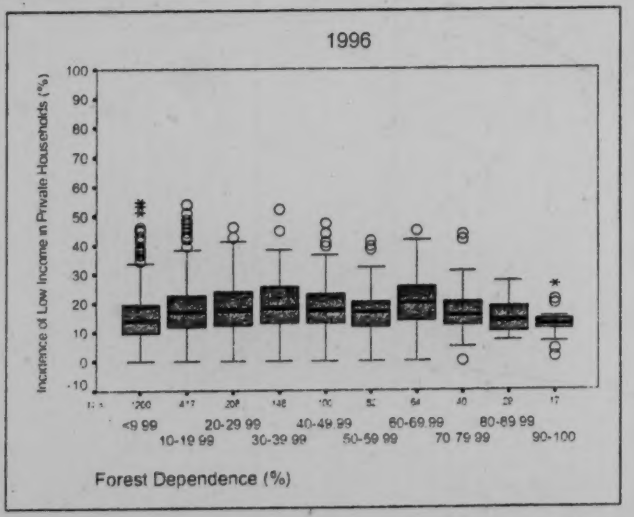
The boxplots in Figure 7 further illustrate the relationship between incidence of low income among people living in private households and forest dependence. For 1986 and 1991, there was not much variation in the incidence of low income as the degree of forest dependence increased. However, in 1996 the incidence of low income among people in private households increased slightly for the CSDs in the 60-69.99% forest dependence class, and declined in the three remaining higher dependence classes. As with median household income, it is difficult from these plots to characterize the

relationship between this incidence of low income and forest dependence. The correlation analysis in a later section may provide a less ambiguous answer.

Figure 7: Boxplots of Incidence of Low Income among People Living in Private Households by Degree of Forest Dependence among Forest Dependence CSDs







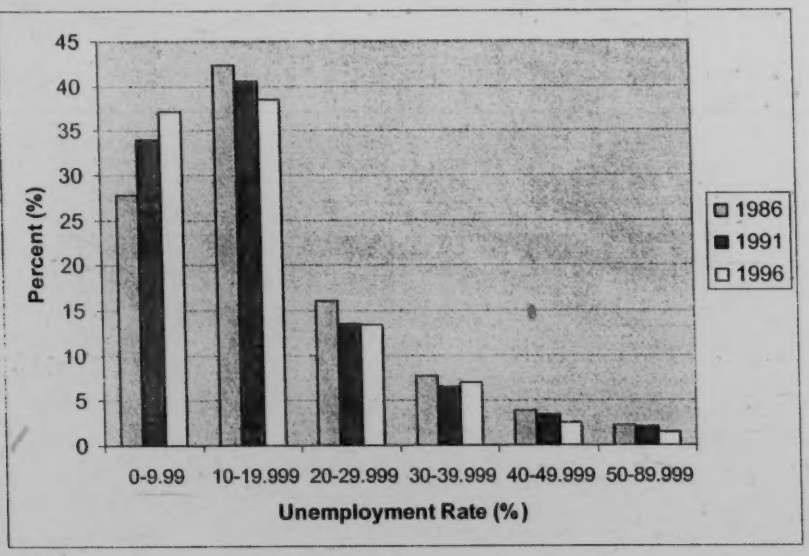
* = extreme
O = outlier

4.1.4 Resilience Measures

4.1.4.1 Unemployment

The unemployment rate is one example of a resilience indicator and it is reported in the Canadian census for each CSD. This statistic refers to the proportion of the total labour force in the CSD that is unemployed in the week prior to enumeration. The 'unemployed' represents people 15 years or older (excluding institutional residents), who were "...without paid work and were available for work and either: (a) had actively looked for work in the past four weeks; or (b) were on temporary lay-off and expected to return to their job; or (c) had definite arrangements to start a new job in four weeks or less." Since the 'unemployed' is only measured for the week prior to enumeration, it represents only a 'snapshot' in time in regards to the composition of this group. Due to the seasonality of some jobs, such as those in the forestry industry, the number unemployed may be overstated. The fact that people with reasons such as points (b) and (c) in the definition are included in the number of unemployed people further explains how the unemployed picture of a CSD could be skewed, although Statistics Canada reports that people in these two categories only comprise a small proportion of the unemployment rate calculation (Statistics Canada, 1999). It should also be noted that this definition of unemployment does not include discouraged workers who had to relocate to find work, involuntary part-time workers, and underemployed workers. The distribution of the unemployment rate among the forest dependent CSDs in shown in Figure 8.

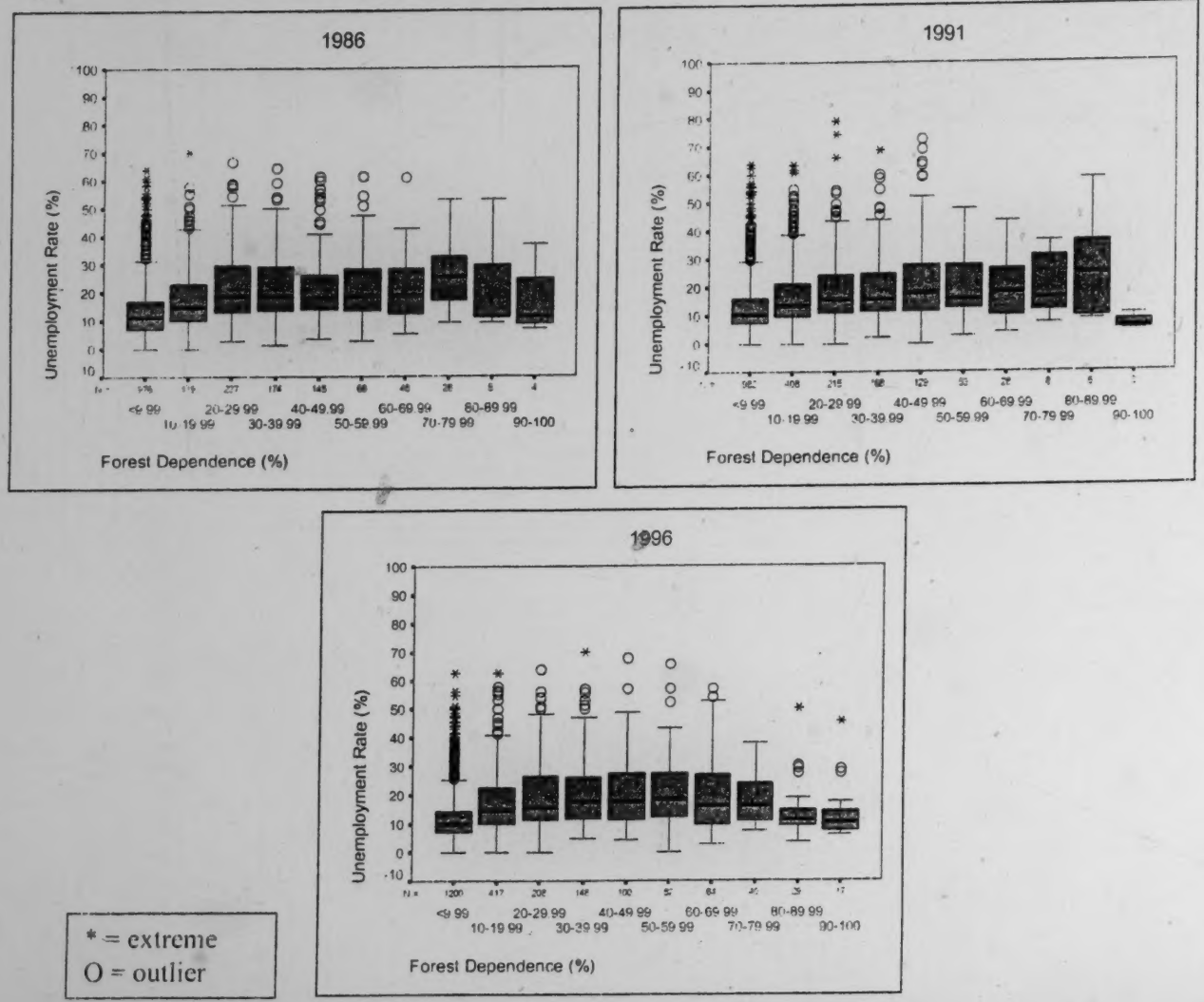
Figure 8: The Percent Distribution of the Level of Unemployment among Forest Dependent CSDs



It is apparent that the proportion of CSDs with higher unemployment rates declined over time, which explains some of the increase in the 0-9.99% category.

The relationship between the unemployment rate and degree of forest dependence can be explored by using the boxplots of these two variables displayed in Figure 9. Ignoring the top two dependence classes for 1986 and 1991, there was an increase in unemployment as forest dependence increased. In 1996, this was the case for the first few classes, but in the higher forest dependence classes, there was a decline in the rate of unemployment for those CSDs. This decline in the higher dependence classes might be attributed to the 1996 increase in the forestry price indexes which in turn reflect improved economic conditions and job opportunities in the forest sector. If these CSDs responded by increasing their forestry activity, this may have caused the unemployment rates to decrease. However, overall these graphs suggest that as forest dependence increases, so does the rate of unemployment.

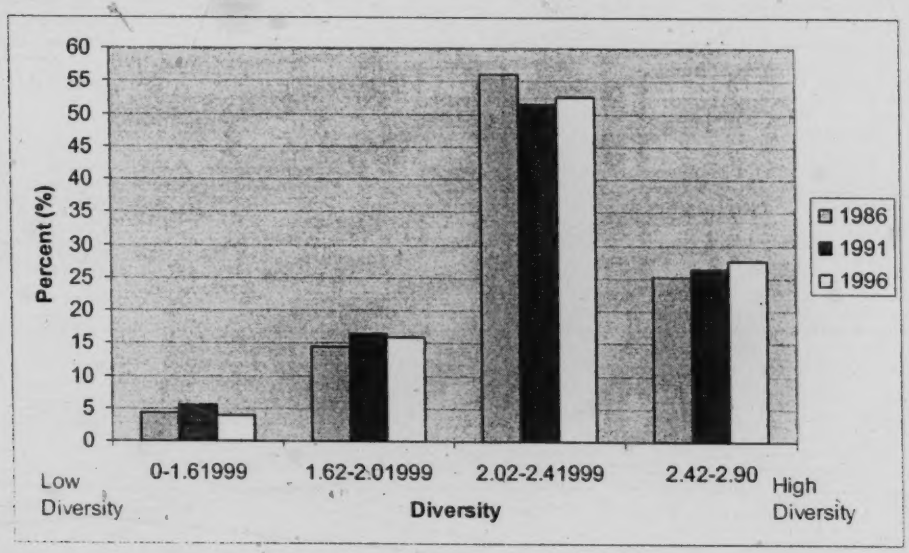
Figure 9: Boxplots for Unemployment by Degree of Forest Dependence among Forest Dependent CSDs



4.1.4.2 Economic Diversity

As a measure of the mix of employment or employment income across sectors, economic diversity is a good indicator of the CSDs' resilience to economic shocks. The nature of its measurement (economy-wide) also makes economic diversity highly preferable to other indicators of the employment or employment income in a particular sector. There are two common ways to calculate diversity – one method uses employment in each of the sectors and the other uses the level of employment income in each of the sectors. Diversity was calculated both ways and the resulting measures were highly positively correlated. Thus, either diversity calculation can be used for analysis. Below, the focus is on diversity using employment incomes, as the definition of forest dependence also used employment income in its base calculations. The distribution of economic diversity among the forest dependent CSDs is shown in Figure 10.

Figure 10: The Percent Distribution of Economic Diversity among Forest Dependent CSDs

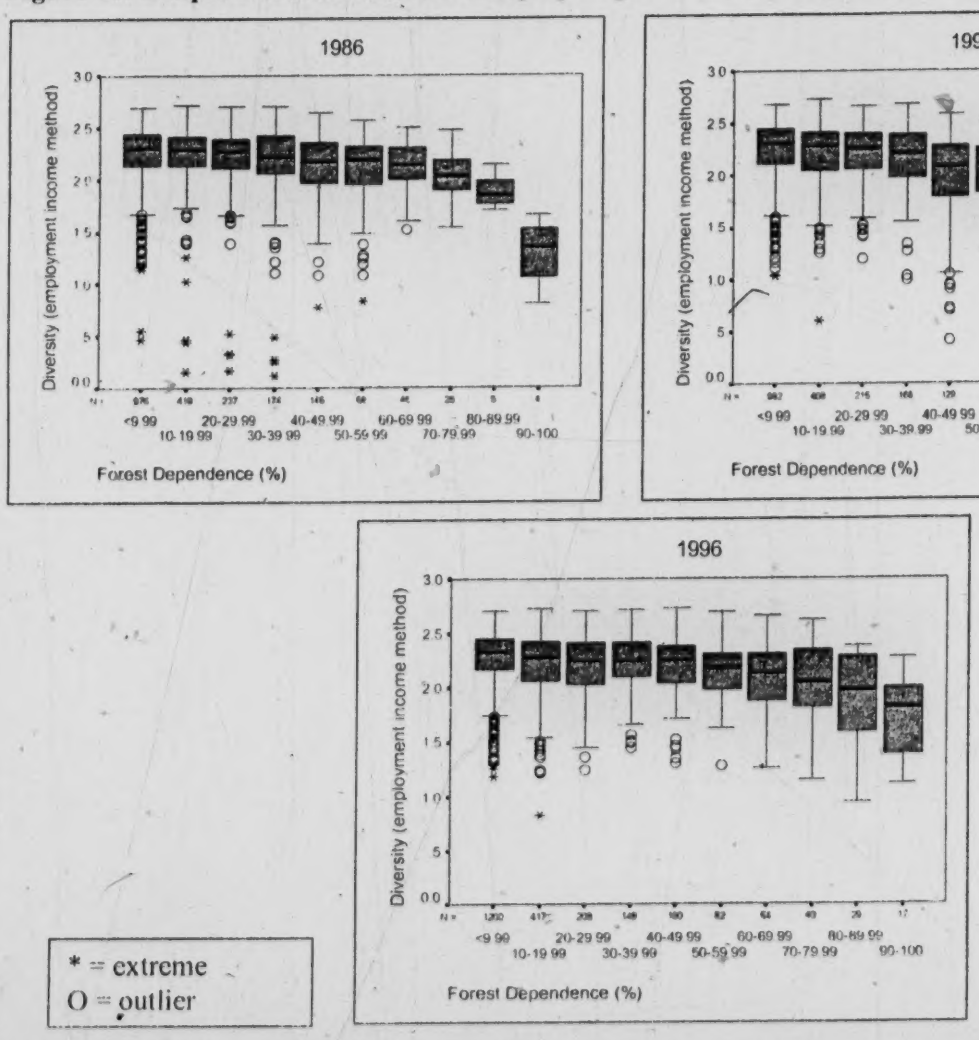


As mentioned earlier, the calculation of diversity using employment income can take a value of zero if all of a CSD's economic activity is concentrated in one sector. In

turn, the maximum value of diversity possible is ln(18) = 2.89, with 18 being the number of economic sectors in each CSD. Thus, Figure 10 shows that in each census year, over 50% of the forest dependent CSDs exhibited moderately high diversity, while the other 25% enjoyed high diversity despite some reliance on forestry or forest related activities. The remaining 20-25% of CSDs in each year exhibited low to very low diversity. The distribution of CSDs among the economic diversity classes is similar in each of the three census years.

The boxplot in Figure 11 also portrays the relationship between diversity and forest dependence. As expected, as forest dependence increases, economic diversity decreases. This suggests that there is a negative correlation between forest dependence and diversity. Thus, an increase in forest dependence in a CSD may bring the risk of decreased resilience to economic shocks.

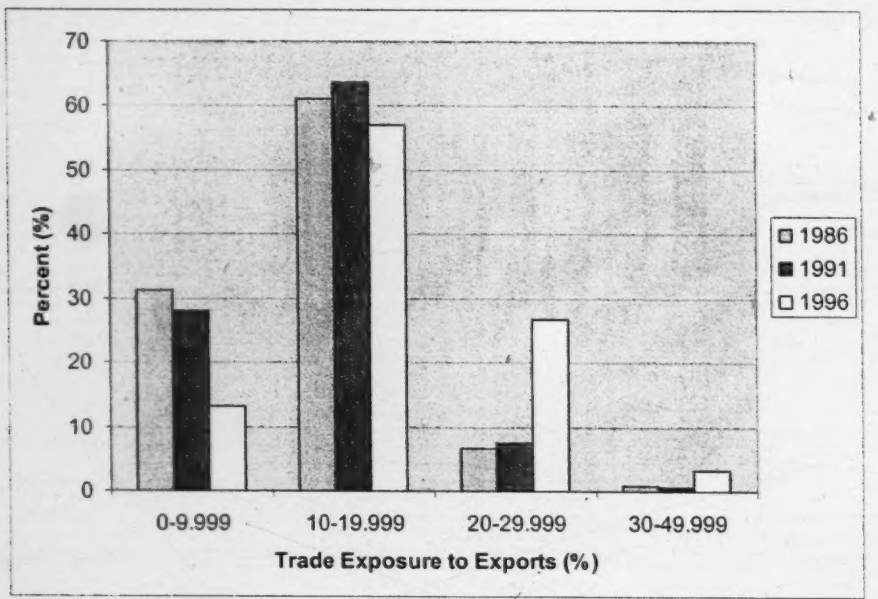
Figure 11: Boxplots of Economic Diversity by Degree of Forest Dependence among Forest Dependent CSDs.



4.1.4.3 Trade Exposure to Exports

Also mentioned above, a CSD's trade exposure to exports can make its local economy vulnerable to fluctuations in global market shocks and exchange rate influences. Trade exposure can be calculated from employment or employment income in each of the economic sectors. To maintain consistency with other variables, trade exposure to exports was derived using employment income. The distribution of trade exposure to exports among the forest dependent CSDs is depicted in Figure 12.

Figure 12: The Percent Distribution of the Level of Trade Exposure to Exports among Forest Dependent CSDs

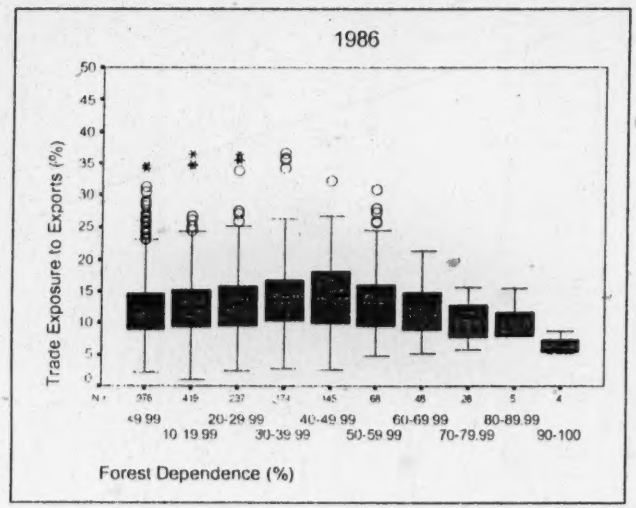


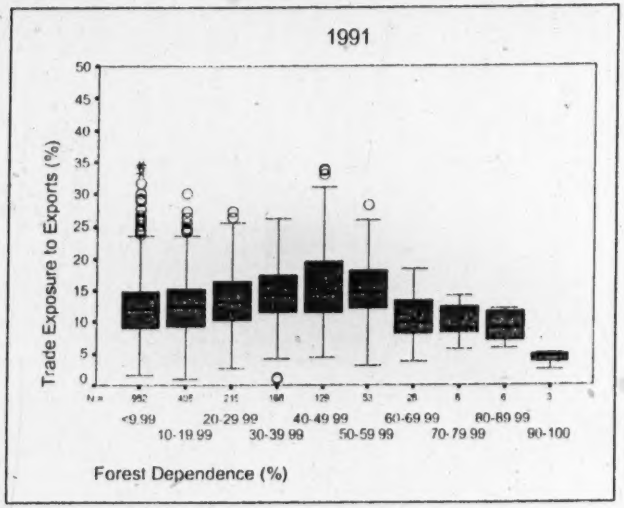
Between 1986 and 1991 there was a slight shift in distribution from the lowest category of trade exposure to exports to the higher categories. However, in 1996 there was a marked increase in trade exposure to exports among the forest dependent CSDs.

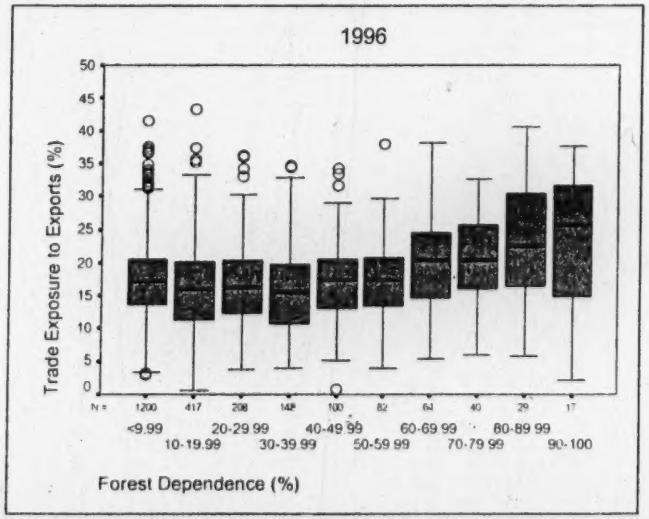
This relationship between trade exposure to exports and forest dependence is further examined in Figure 13. In 1986 and 1991, as forest dependence increased, trade exposure to exports increased up to the 50% dependence level, and steadily declined for

each subsequent dependence class. However, quite a different result is seen in 1996. As forest dependence increased, trade exposure to exports markedly increased throughout all of the dependence classes. The increase in forest products price indexes between 1991 and 1996 likely explains the shift towards more reliance on exports, as forestry companies tried to maximize their economic opportunities in the external markets. Hence, forest dependence seems to be positively correlated to a CSDs trade exposure to exports. Thus, throughout the time series examined in this thesis, the CSDs were becoming more susceptible to outside economic shocks.

Figure 13: Boxplots of Trade Exposure to Exports by Degree of Forest Dependence among Forest Dependent CSDs





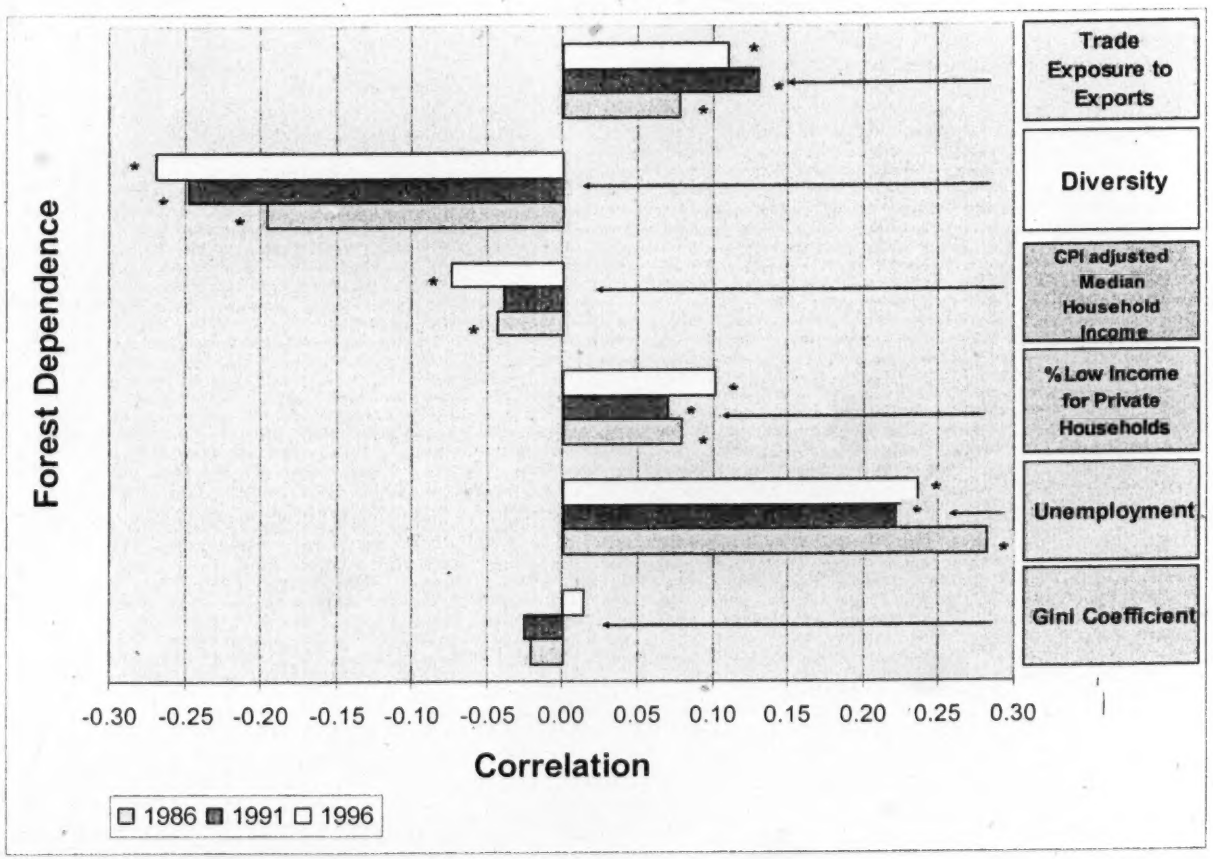


* = extreme
O = Outlier

4.1.4 Correlation between forest dependence and various indicators

Observing the correlations between forest dependence and each of the economic sustainability indicators provides additional insights into the relationships that exist between these indicators. In fact they can clarify the conclusions that were drawn in the previous section. Significance was determined from the Pearson's correlation coefficient (r). As a measure of linear association, these coefficients range in value from -1 (a perfect negative relationship) to +1 (a perfect positive relationship). A value of zero indicates no linear relationship (Berenson and Levine, 1996).

Figure 14: The Degree and Direction of Correlation between Forest Dependence and Other Variables in Forest Dependent CSDs*



* signifies that *r* is significantly different from 0 at the 5% level

A graph of these correlations and their significance is shown in Figure 14. Trade exposure to exports, incidence of low income among people living in private households, and unemployment are all positively correlated with forest dependence. Diversity, median household income, and income inequality (Gini coefficient values) are negatively correlated with forest dependence. All of the correlation coefficients are statistically significant at the 0.05 level, except the Gini coefficient for all three years and the median household income in 1991. To draw conclusions, the frequency, boxplot and correlation graphs for each indicator will be compared and studied in relation to forest dependence.

4.1.5.1 Median Household Income

From Figures 2 and 3, it was difficult to clearly define the relationship between median household income and forest dependence. Figure 2 showed only an increase in the number of CSDs with higher median household income over time. The boxplots in Figure 3 were used to examine the distribution of CSDs' median household income across the forest dependence categories. However, the distribution was relatively stable for 1986 and 1991, and 1996 showed a positive relationship between the two variables in only the highest forest dependence categories. However, Figure 14 shows that median household income is negatively correlated to forest dependence. The correlation was significant in 1986 and 1996, but not in 1991. This negative correlation should be evaluated carefully as correlations imply an association and not necessarily causal structure. As such, other forms of statistical analysis may be required to accurately portray the relationship between median household income and forest dependence.

4.1.5.2 Gini Coefficient

The boxplots of Gini coefficient values against forest dependence showed that the distribution of Gini coefficient values was relatively stable over the forest dependence categories across each year. This result is explained in Figure 14. Although the Gini coefficient was negatively correlated to forest dependence in 1986 and 1991, and positively correlated in 1996, the correlation coefficients are not significant in any year. Thus, there appears to be no significant relationship between Gini coefficient values and forest dependence. Thus, other factors must affect the Gini coefficient. Sharpe and Zyblock (1997) found that income inequality (as measured by the Gini coefficient) was highly dependent on the business cycle and other structural factors such as unemployment.

4.1.5.3 Incidence of Low Income Among People in Private Households

As with median household income, the boxplots in Figure 7 did not clearly characterize the relationship between the incidence of low income among people living in private households and forest dependence. The correlation analysis provided a less ambiguous answer. The incidence of low income among people living in private households was positively and significantly correlated to forest dependence (Figure 14).

4.1.5.4 Unemployment

The boxplots in Figure 9 of the unemployment rate by degree of forest dependence suggested a trend that as forest dependence increases, the unemployment rates increase as well. This is confirmed in Figure 14. Forest dependence and unemployment levels are positively and significantly correlated.

4.1.5.5 Diversity

Like the unemployment rate, economic diversity showed a clear trend in the Figure 11 boxplots over the time series. As forest dependence increased, there was a downward trend in economic diversity. The correlation analysis confirms this trend. This result is expected; increases in forest dependence mean that forestry and forest-related activity comprise a bigger share of the total economy, thus directly decreasing the CSD's diversity. There is much consensus that this result makes highly forest dependent CSDs less resilient to economic shocks, as well as technical change. Since technical change affects each sector differently, higher diversity in a CSD could help balance employment changes among the different sectors. However, Attaran (1986) argued that the industrial mix of an economy is perhaps more important to its resilience than economic diversity. Attaran (1986) claims that forest dependent communities which have other industries that follow opposite business cycle trends as the forest industry are considered more resilient than if these communities had industries that followed the same trends as forestry. While this may be a valid argument for CSDs of moderate diversity, the impact diversity has on resilience cannot be disputed in the 5-20% of forest dependent CSDs that exhibit low to moderately low diversity.

4.1.5.6 Trade Exposure to Exports

The boxplots of trade exposure to exports and forest dependence in Figure 13 suggested a fairly strong trend in the time series that increased forest dependence was associated with an increase in the CSDs' trade exposure to exports. This was most prominent in 1996. The correlations in Figure 14 confirm this finding. Forest dependence and trade exposure to exports are positively and significantly correlated.

Since trade exposure to exports means a direct reliance on the economy outside the CSD, the increase in trade exposure that accompanies increased forest dependence does make the CSD more vulnerable to outside economic shocks and exchange rate influences.

4.2 A Comparison of Forest Dependent CSDs to Non-Forest Dependent CSDs

The economic sustainability indicators over time in forest dependent communities were examined above. This section presents comparisons of those results to the indicator characteristics in non-forest dependent communities. To summarize the relationship of the indicators to forest dependence, two categories of forest dependence were employed: those CSDs exhibiting positive forest dependence but was less than 50% dependent, and CSDs who were 50-100% dependent on forestry or forest-related activities.

4.2.1 Median Household Income

Figure 15 presents a series of three graphs that compare the distribution of median household income across forest and non-forest dependent CSDs for the time series. The relative stability of median household income across time portrayed in Figure 3 is again depicted here, despite the addition of the non-forest dependent CSDs. There were more extreme values and outliers in the non-forest dependent group, and median household income did not vary much between this group and the groups of CSDs less than 50% forest dependent. However, there was a slight increase in median household income in the groups of CSDs that were more than 50% forest dependent for all three years. There was also a slight increase in the variance of the values in this group (as represented by the height of the boxes) in 1986 and 1991. However, there was a definite decrease in overall variance within this same group of CSDs for all years. This is partially due to the small

number of observations in the >50% forest dependence group. Although the data for median household income may not raise concerns regarding increasing forest dependence, it is difficult to ignore the results of the correlation analysis that link increasing forest dependence with decreasing median household income.

4.2.2 Gini Coefficient

The distribution of Gini coefficient values across forest and non-forest dependence are shown as 3 graphs in Figure 16. Across all three years, there was a decrease in the overall variance of the Gini coefficient as forest dependence increased. In 1986 there was a slight decline in the Gini coefficient as the CSDs became more forest dependent. For reference, this decline would suggest an increase in income equality. In 1991 and 1996, the Gini coefficient remained relatively stable as forest dependence increased. Whether the Gini coefficient was stable or not over the two forest dependence groups, it has already been determined in the correlation analysis that there is not a significant relationship between Gini coefficient values and forest dependence. There are undoubtedly other factors that control the behaviour of this indicator through time.

Figure 15: Boxplots of Comparisons of the Median Household Income across Forest and Non-Forest Dependent CSDs

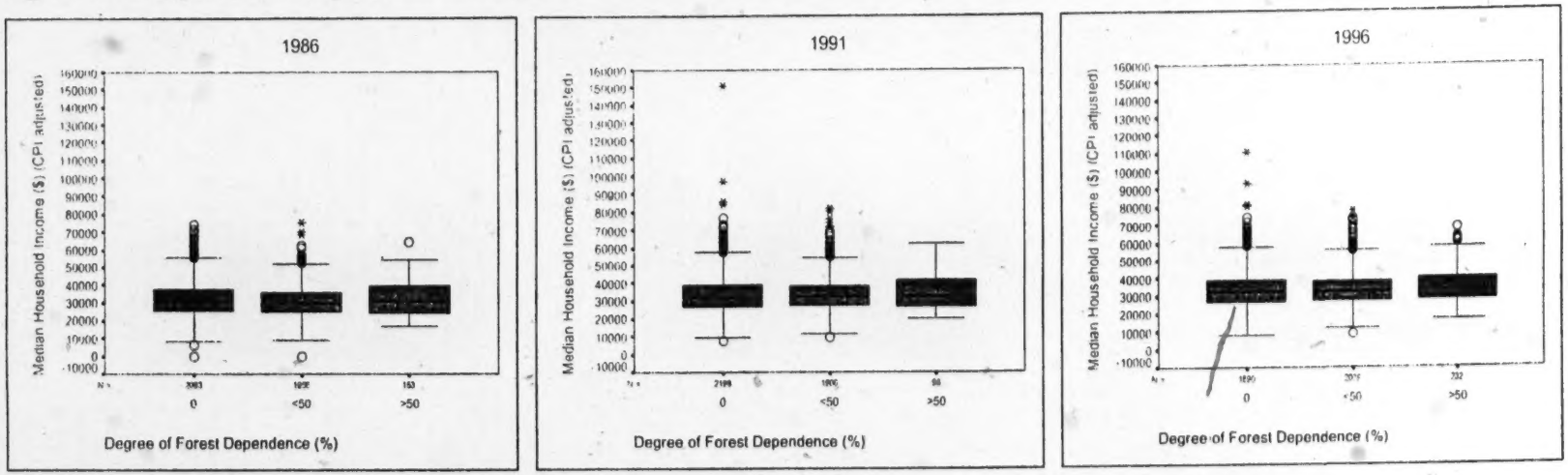
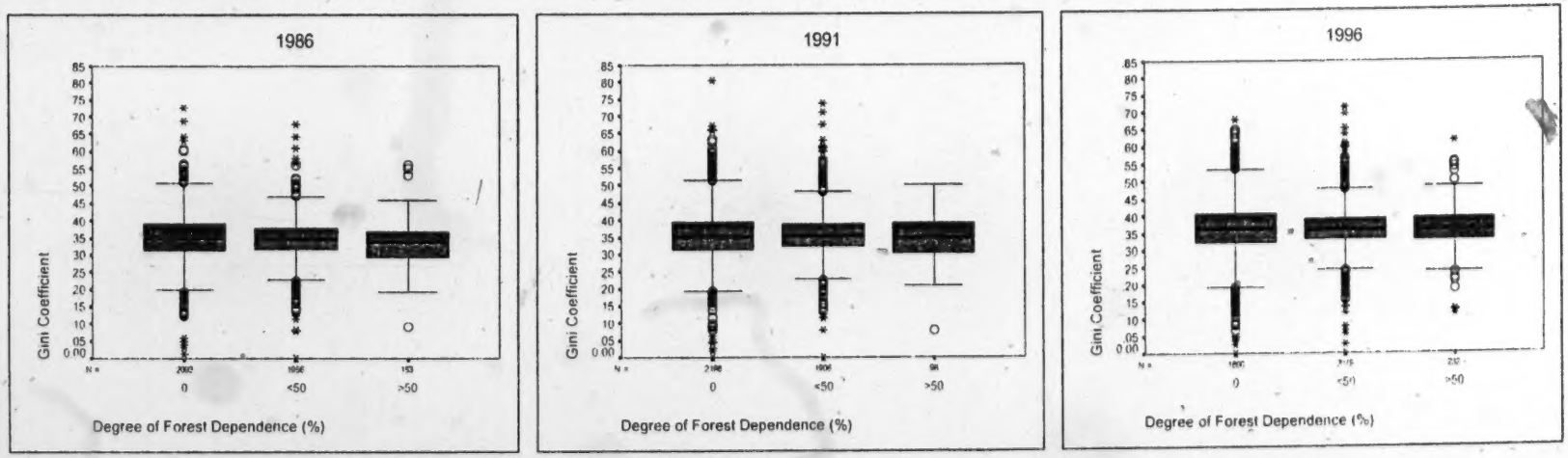


Figure 16: Boxplots of Comparisons of Gini Coefficient Values across Forest and Non-Forest Dependent CSDs



4.2.3 Incidence of Low Income Among People Living in Private Households

Figure 17 shows the incidence of low income among people living in private households and forest dependence across time. A decrease in the overall variance of this indicator as forest dependence increases across all years is observed. Between the two forest dependence groups the distribution of the incidence of low income is very similar across all years. However, the addition of the non-forest dependence group shows more clearly the result seen in the correlation analysis that increases in forest dependence are met with increases in incidence of low income for people living in private households.

4.2.4 Unemployment Rate

The results of the correlation analysis of forest dependence and the unemployment rate are confirmed in Figure 18. This series of graphs compares the distributions of the unemployment rate across forest and non-forest dependent groups of CSDs across all three years. It is clear that as forest dependence increases, so does the unemployment rate. Also, the variance within the middle 50% of the values (as represented by the height of the boxes) increases as forest dependence increases in 1986, 1991, and 1996.

Figure 17: Boxplots of Comparisons of Incidence of Low Income among People Living in Private Households across Forest and Non-Forest Dependent CSDs

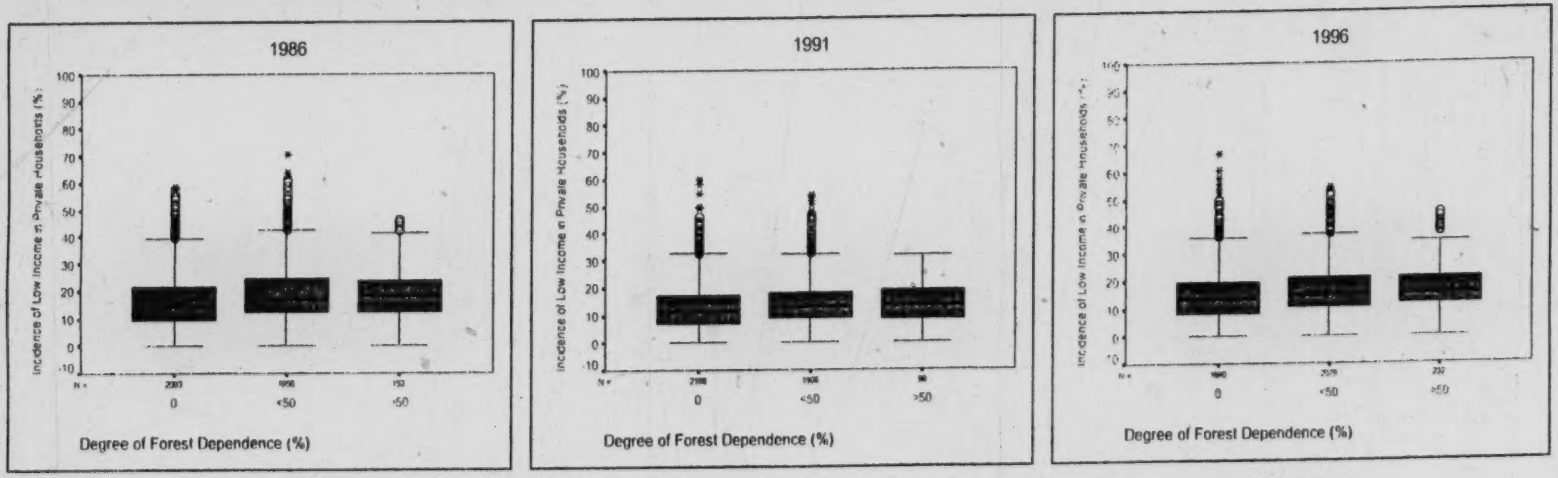
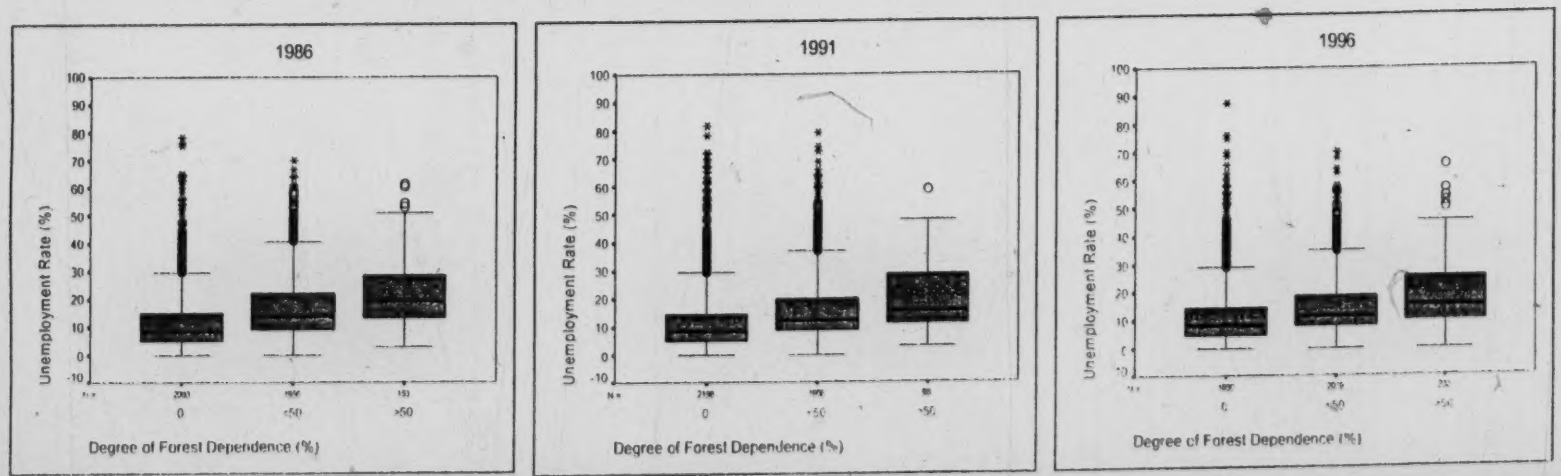


Figure 18: Boxplots of Comparisons of Unemployment Rates across Forest and Non-Forest Dependent CSDs



4.2.5 Economic Diversity

Figure 19 compares the distribution of economic diversity to forest dependence across the three census years. Compared to the non-forest dependent groups of CSDs, diversity increased in all three years for the second group with less than 50% forest dependence. This could probably be explained by the addition of activity in Division C (logging and forestry) and/or part of Division E (forestry related manufacturing), both of which are absent in the non-forest dependence group. The addition of this activity increases the diversity of the CSDs in this group that is less than 50% forest dependence. However, in the third group that is more than 50% dependent on forestry or forest-related activity, there is a definite decline in diversity in all three years. This confirms the correlation result that increased forest dependence is related to decreased diversity.

4.2.6 Trade Exposure to Exports

Figure 20 compares the distribution of trade exposure to exports to forest dependence across the time series for the three groups of CSDs. Trade exposure to exports definitely increased from the non-forest dependent group to the two forest dependent groups. However, in 1986 and 1991, the same trend is seen as in Figure 13; trade exposure increases for the group that is less than 50% dependent upon forestry or forest-related activity, but decreases in the third, more forest dependent group. Examining 1996, again the same trends are seen as in Figure 13, but the results differ greatly from the other two years. As CSDs become increasingly forest dependent, their trade exposure to exports increases as well. This is the same relationship exemplified in the correlation analysis (Figure 14).

Figure 19: Boxplots of Comparisons of Economic Diversity across Forest and Non-Forest Dependent CSDs

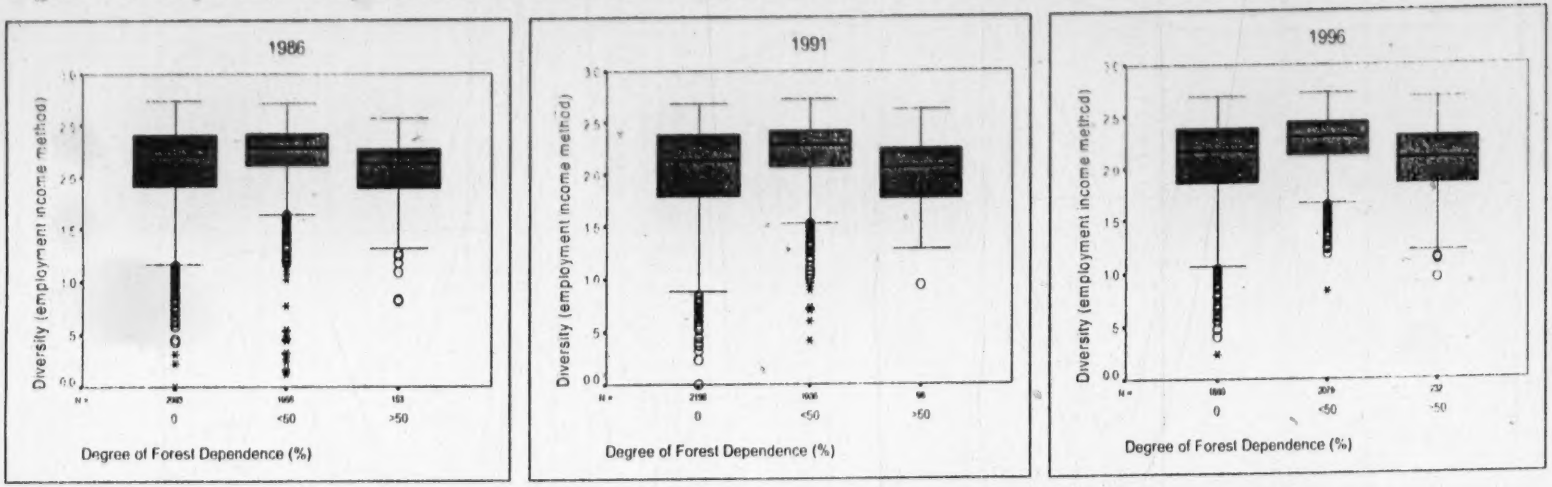
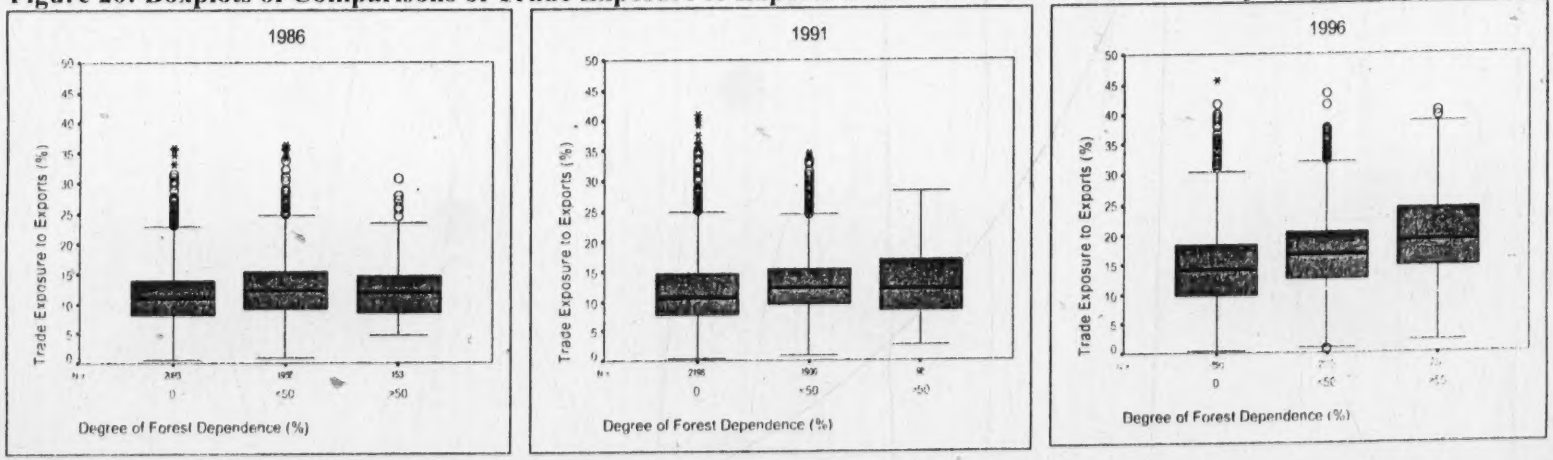


Figure 20: Boxplots of Comparisons of Trade Exposure to Exports across Forest and Non-Forest Dependent CSDs



5 ECONOMETRIC MODEL ESTIMATION, RESULTS, AND DISCUSSION

A central issue in sustainable forest management is the relationship between economic indicators and the degree with which a community becomes dependent on the forest industry. This suggests that forest dependence per se. is not an indicator, but it does affect economic indicators in certain ways.

The central research questions this study attempted to answer with empirical models were: 'How does forest dependence in a CSD affect key economic indicators such as incidence of poverty, income inequality, the unemployment rate, and median household income holding constant aggregate demand, trade exposure and other important factors? Is there anything unusual about how forest dependence affects other indicators? How do other variables such as economic diversity, trade exposure, and aggregate demand affect indicators at the CSD level? Thus, the central research questions were posed accordingly to reflect the investigation of the relationships among indicators in a forest dependent community, with forest dependence as an exogenous variable.

The purpose for developing economic models in this study is to define the relationships that may exist between the economic sustainability variables of interest. The empirical models developed in this study are useful because the regression approach examines the relationship between two variables holding the other variables in the model constant. Since the correlation analysis performed in Chapter 4 does not by nature allow for this, the empirical models are a necessary step in order to more formally define the relationships between the variables. Model specification and results from previous

studies were used in specifying a desirable model. The first part of this chapter will outline examples of such studies and provide their backgrounds, which were used to begin specifying this study's economic models. The remainder of this chapter will focus on the full specification of the empirical models, their estimation and results.

5.1 Review of Previous Studies

5.1.1 The Berck model

Berck *et al* (2000) analyzed how policies protecting old growth forests affected timber dependent communities. They wanted to see if long run changes in timber-related employment would cause economic downturn in other sectors and increases in participation in federal poverty programs. The authors used monthly time series data from 1983-1993 for 11 counties in California. Three research questions were posed: (1) at the county level, do decreases in timber employment cause a long run increase in poverty program participation and a long run decrease in employment in other sectors? (2) is there a differentiation in the role county timber jobs can play (versus other county jobs) in reducing poverty program participation and inducing county employment growth in the short run? and (3) are the long run determinants of county employment and poverty factors at the county, or at the aggregate state level? Thus, Berck *et al* (2000) examined the relationship between poverty program participation and employment at the county and multi-county region as well as the effect aggregate demand had on county level variables. Poverty, employment and aggregate demand variables are of interest in sustainability assessments. These three types of variables will also play an important role in the empirical models of this thesis.

While there was substantial literature at the state and national level outlining a positive relationship between the rate of unemployment and poverty rates and poverty program participation, Berck *et al* (2000) wanted to discover whether this relationship held at the county or at least multi-county level. The first and second research questions are drawn from economic base theory that state that expansion in exporting sectors, such as lumber production produces higher employment base multipliers than growth in non-exporting sectors. Thus, the authors test the hypothesis that timber-related employment plays a different role in county poverty reduction than that of employment growth in other economic sectors. To answer the third research questions, Berck *et al* (2000) used total monthly state employment as a proxy for aggregate demand. It is believed that aggregate demand is a significant factor influencing demand for local employment, as well as the willingness of the unemployed to move elsewhere for employment. This is due to the fact that aggregate demand acts as a proxy for total economic activity. Local economic activity can increase if state economic activity increases. The research questions posed in the Berck *et al* (2000) study are similar to those presented in the study for this thesis. However, the two studies differ in the methodology used to investigate the research problems.

In order to address the research questions, Berck *et al* (2000) constructed a two sector empirical model. The model represents economic relationships that are thought to determine the impacts of changes in state economic conditions and changes in county employment on local level poverty. The model consisted of six equations. The first equation represented equilibrium in the county timber labour markets:

$$T^d(w_T, SE) = T^s(pop, w_T, w_N) \qquad [11]$$

where T^d = county timber industry labour demand, w_T = timber industry wage, SE = state employment, T^s = county timber industry labour supply, pop = county population, and w_N = non-timber wages. Equation [11] reflects the fact that state employment (aggregate demand) shifts demand for labour (as aggregate demand can be a substitute for local workers).

The second equation in the empirical model represented equilibrium in the non-timber labour markets where both state employment and county timber employment shift demand:

$$N^d(SE, T, w_T) = N^s(pop, w_T, w_N) \qquad [12]$$

where N^d = demand for county workers in non-timber industries, T = local timber sector, and N^s = supply of county workers in non-timber industries. This equation reflects economic base theory in that the county timber sector (a primary exporting industry) should drive the demand for county labour in the study's 11 timber-dependent counties.

The third equation in the system defined the relationship between county poverty and other variables:

$$POV = POV(N, T, pop, mig, SPOV) \qquad [13]$$

where POV = county poverty program caseload, mig = county net migration, and SPOV = state poverty program caseload. Migration was included to capture the unemployed workers who leave the county in search of employment. State poverty program caseload in this equation acts as a proxy for non-county factors that may influence participation in the county poverty program. These non-county factors can be things such as state-wide changes in eligibility requirements or benefits levels. The state level variables are

defined in equations [14] and [15] with total state employment characterized in equation [14] and state poverty program caseload in equation [15]:

$$SE = SE(SE_{t-1}, SE_{t-2}) \quad [14]$$

$$SPOV = SPOV(SE_{t-1}, SE_{t-2}, SPOV_{t-1}, SPOV_{t-2}) \quad [15]$$

The final equation in the empirical model defined county level migration as a function of other county and state variables:

$$mig = mig(SE, N, T, POV, SPOV) \quad [16]$$

Since monthly county wage, migration data, and annual county population data were unavailable, the authors solved the empirical model to eliminate these variables. This produced a co-integrated vector autoregressive (VAR) model. Berck *et al* (2000) solved this VAR model in order to provide answers for the three initial research questions. In determining the relationship between timber-related employment and county poverty, the authors used participation in three different federal poverty programs, including the Food Stamps program. The three programs differed from each other in terms of their eligibility requirements. In the counties and multi-county regions studied, the authors found mixed evidence that timber employment decreases were associated with increases in Food Stamp program participation. For the two other federal poverty programs, Berck *et al* (2000) found little evidence at the county or multi-county region level that decreases in timber employment were associated with increases in program participation in either the short or long run.

The authors also wanted to determine whether timber-related employment acted as an economic base for the county generating larger increases in employment than jobs in other sectors. Thus, Berck *et al* (2000) used actual and simulated model forecasts to

predict poverty program participation conditional on increases in timber and non-timber related employment. Although the model showed that timber employment has a different effect than non-timber employment on long run levels of county employment and poverty, the timber sector base multiplier effect is most likely quite small.

The strongest conclusion from the study was that a long run relationship does exist between state and county variables. Specifically, there was a significant long run relationship between state employment levels and state poverty program participation to participation in county poverty programs. For policy purposes, the authors concluded that policies protecting old growth ecosystems are unlikely to have a significant effect on county unemployment and poverty levels. These two variables are influenced by state-wide economic conditions and state poverty program structures (Berck *et al*, 2000). Thus, the link between some county policies and county indicators is uncoupled.

This study confirms some of the assertions that were made in Chapter 2 regarding to the choice of scale for sustainability assessments. The interdependencies between the county and state sociopolitical levels made it necessary for Berck *et al* (2000) to develop their study using both these scales. Also, the study supports the notion that the chosen scale of the indicator is related to the broader policy or management context. In using the county, multi-county and state levels as the scales of the analytical unit, these authors were able to determine that some county variables were influenced by economic activity at the state level.

5.1.2 The Osberg Model

Another interesting set of models can be found in Osberg (2000), which

theoretically builds upon Berck *et al*'s (2000) models with the addition of a poverty intensity variable. Osberg (2000) sought to determine the reason for the convergence of poverty intensity in the United States and Canada for the years of 1994-1997. Despite the wide range of poverty measurements that exist in the literature, Osberg argued that most do not exhibit the "...properties that an ethically defensible index of poverty should possess." (Osberg, 2000). Therefore, the author chose to use the Sen-Shorrocks-Thon (SST) index of poverty which displays the necessary properties such as focus, replication invariance, symmetry, monotonicity, and transfer sensitivity. SST is defined as:

$$SST = (RATE)(GAP)(1 + G(X)) \quad [17]$$

where RATE = the poverty rate (percentage of the population with incomes below the poverty line), GAP = the average poverty gap ratio (average percentage gap between the incomes of the poor and the poverty line), and G(X) = the inequality in poverty gaps (the Gini index of inequality of the poverty gap among all people where the poverty gap of the non-poor is set to zero). Considering the fact that G(X) is usually empirically small, and also considering the advantages to changing the functional form, Osberg (2000) preferred the specification of poverty intensity (when measuring changes over time) that can be approximated as the sum of the percent changes of the poverty rate and the average poverty gap ratio:

$$\Delta \ln(SST) = \Delta \ln(RATE) + \Delta \ln(GAP) \quad [18]$$

Osberg (2000) attempted to uncover what factors are responsible for the convergent trend in poverty intensity rates in Canada and the United States between 1994 and 1997. For example, the SST indexes for Canada were 5.89 and 7.00 for 1994 and 1997 respectively, while the SST numbers for the United States were 12.59 and 10.64

respectively. In order to explain this convergence, Osberg (2000) noted that during the 1990s there were significant changes in international trade exposure, social policy and macro economic conditions in both Canada and the United States. As such, attention was given to these factors in this study.

When poverty is discussed in the literature, there are mixed feelings about where to draw the poverty line and how it should be revised over time. In addition, there is also dispute as to whether the poverty line should be seen as 'relative' or 'absolute'. To test the robustness of results, Osberg (2000) performed one set of regressions with the dependent variable using the definition of the poverty line as the internationally accepted standard of one-half median equivalent individual after-tax income. The second set of regressions had a dependent variable using a poverty line as determined by the before-tax Low Income Cut-Off (LICO) as defined by Statistics Canada. As mentioned in Chapter 4, the LICO defines families whose expected expenditure of food, clothing and shelter (as a share of income) are more than 20% greater than the national average while controlling for city and family size.

The former set of regressions (which uses a relative poverty line) implied a much lower poverty rate than use of the LICO concept of poverty (an absolute poverty line); as such 50% of the median is often criticized as being too low. The first and second set of regressions that were formulated to explain the changes in poverty intensity in Canada and the United States are outlined in equations [19] and [20]:

$$\text{Poverty line}_{med} = \Delta \text{ unemploy} + \Delta\text{avgUI} + \Delta\text{propUI} + \Delta\text{socialassist} + \Delta\text{importexp} + \Delta\text{exportexp} \quad [19]$$

$$\text{Poverty line}_{LICO} = \Delta \text{ unemploy} + \Delta\text{avgUI} + \Delta\text{propUI} + \Delta\text{socialassist} + \Delta\text{importexp} + \Delta\text{exportexp} \quad [20]$$

where unemploy = male aged 25-54 unemployment rate, avgUI = average weekly unemployment insurance (UI) benefits/beneficiary, propUI = the proportion of unemployed that receive UI, socialassist = social assistance variable (ex. welfare), importexp = import exposure, and exportexp = export exposure. For equations [19] and [20], Osberg (2000) also performed an extra regression for each one, replacing the linear specification of the unemployment rate with its log form. By including the trade exposure variables, Osberg (2000) tested the hypothesis that the convergence in poverty intensity can be explained by trade liberalization. Osberg (2000) was doubtful that this hypothesis will hold in the case of poverty due to the fact that the income inequality and poverty outcomes across Canada and the United States are heterogeneous. This heterogeneity can be partially explained by the different anti-poverty programs that exist at the local level, even though evidence shows that they are not costly to implement. Since import and export exposure are both parts of the trade dependence story, Osberg (2000) included them in the regressions to determine the independent impact of trade exposure on poverty intensity. Thus, the central research question in this study was whether the changes in poverty intensity across provinces and states from 1994 to 1997 could be explained by changes in trade exposure, social assistance, aggregate unemployment, or unemployment insurance.

From equations [19] and [20], the primary difference in the regression results was that the social assistance and unemployment insurance coefficients were larger with the 'absolute' poverty line than when the poverty line was measured in relative terms. Overall, in both regressions, the estimated coefficients had the expected sign, were significant and of conceivable magnitude. In addition, both the logarithmic and linear

forms of the unemployment variable showed that a decrease in unemployment would result in a decrease of poverty intensity. As predicted by the author, the trade exposure variables were not significant in the regressions. This result is consistent with the heterogeneity of social policies and poverty outcomes across the provinces and states, despite many years of free trade. The overall outcome of the study suggested that social assistance, unemployment insurance and the macro economic conditions are all important determinants of the observed changes in poverty intensity in Canada and the United States in the 1990s (Osberg, 2000).

5.2 Empirical Models of Key Economic Indicators

Since the theoretical background employed in this thesis research is somewhat similar to that in the above studies, it is possible to use the Berck *et al* (2000) and Osberg (2000) studies to formulate hypotheses of what relationships may be found in the census dataset. In the present study, forest-related activity was captured by the forest dependence index, which is partially measured with the proportion of employment income in the CSD that is derived from forestry related industries (see section 3.2.2). This differs from Berck *et al* (2000) who used only timber-related employment to measure forest-related activity. In addition, the census data included the incidence of poverty recorded among people living in private households, while Berck *et al* (2000) measured poverty by the participation rates in poverty programs. Thus, the measures in this present study and the related variables in Berck *et al* (2000) are somewhat different. Nevertheless, based on the results in Berck *et al* (2000), it may be hypothesized that forest dependence will not be significantly related to the unemployment rate and the

incidence of poverty variable. In turn, it might be expected that aggregate demand (as measured by provincial employment) has a significant relationship with both the unemployment rate and the incidence of poverty in private households.

In Osberg's (2000) study, the poverty intensity index calculated is different from the incidence of poverty variable used in the present study. However, the index is partially measured using a poverty line based upon LICO, which is also used to derive the incidence of poverty measure for CSDs. By examining the main conclusions from Osberg (2000), it could be hypothesized that a significant positive relationship exists between the unemployment rate and the incidence of poverty. Also, it might be expected that the trade exposure variables in the present study will not have a significant relationship with the incidence of poverty for people in private households.

Both Berck *et al* (2000) and Osberg (2000) explore important economic relationships that provide support for the specification of this study's empirical models. The models estimated here are based on the dataset of three census years of data at the CSD level for 4202 CSDs across Canada. Although geographically there are 10 provinces and 2 territories for the 1986-1996 census, the effect of a CSD located in the Yukon Territory could not be captured due to the small number of Yukon CSDs in the final dataset. The relationships shown in Berck *et al* (2000) and Osberg (2000) are explored with this study's data in an attempt to uncover relationships that may exist between other important economic variables that might help answer this study's central research questions.

5.2.1 Specification #1 (Approximation of Berck *et al's* (2000) models)

First, similar to Berck *et al* (2000), a reduced form two sector, empirical model was developed. The main focus was on the CSD level, with the second sector at the provincial level where total provincial employment was used as a proxy for aggregate demand. The influence of the forest sector was tracked using the Forest Dependence Index. The resulting structural relationships were examined with three models, each examining different economic relationships. All of the models were estimated as Random Effects models, so their equations are structured accordingly.

The first model is:

$$UNEMPR_{it} = \beta_1 + \beta_2 FORDEP_{it} + \beta_3 MEDHINC_{it} + \beta_4 GINI_{it} + \beta_5 TEEXP_{it} + \beta_6 DIV_{it} + \beta_7 PROVEMP_{it} + \beta_8 D_{1t} + \ldots + \beta_{17} D_{10t} + \mu_i + \epsilon_{it} \quad [21]$$

where i = CSD index, t = time index, UNEMPR = unemployment rate, FORDEP = % of economy that is forest dependent, MEDHINC = median household income, GINI = Gini coefficient of income inequality, TEEXP = % trade exposure to exports, DIV = economic diversity (calculated with employment income), PROVEMP = total provincial employment, and $D_1 \ldots D_{10}$ = 9 provincial and 1 territory dummy variables (with Ontario representing the omitted dummy variable). The purpose of this first model is to test the relationship between the unemployment rate and forest dependence. This was modeled after Berck *et al*'s (2000) equations that attempted to uncover the relationship between forest sector employment and unemployment rates in the counties studied.

The remaining models in Specification # 1 are:

$$MEDHINC_{it} = \beta_1 + \beta_2 FORDEP_{it} + \beta_3 UNEMPR_{it} + \beta_4 GINI_{it} + \beta_5 DIV_{it} + \beta_6 PROVEMP_{it} + \beta_7 D_{1t} + \ldots + \beta_{16} D_{10t} + \mu_i + \epsilon_{it} \quad [22]$$

$$GINI_{it} = \beta_1 + \beta_2 FORDEP_{it} + \beta_3 MEDHINC_{it} + \beta_4 UNEMPR_{it} + \beta_5 DIV_{it} + \beta_6 PROVEMP_{it} + \beta_7 D_{1t} + \ldots + \beta_{16} D_{10t} + \mu_i + \epsilon_{it} \quad [23]$$

These three models were also estimated with an alternate specification. Interaction terms between FORDEP and regional/provincial dummy variables were added to the original models. This is to account for some of the heterogeneity that may exist across regions for Canada. For example, in eastern Canada, the CSDs are more numerous and smaller in size compared to the CSDs in western Canada. Thus, this alternate specification for all three of the models attempts to determine if any of the relationships between FORDEP and other variables shows some differences across regions or provinces. The geographic regions/provinces in Canada (used in addition to the set of provincial dummy variables) used in this alternate specification are: BC, PRAIR (AB, MB, SK), ON, QUE, MARI (NFLD, PEI, NS, NB), NWT. The two regional dummy variables were created due to the similarities in forestry in their component provinces, while the rest of the provinces stand alone due to their heterogeneity in terms of forestry issues. Interaction terms were created with each of the new regional/provincial dummy variables by multiplying them by the FORDEP variable for each CSD. These interaction terms were added to each of the three models with the Ontario interaction term being left out of each of the models.

5.2.2 Specification #2 (Approximation of Osberg (2000) linear models)

Just as one model in Specification #1 was structured from some of Berck *et al*'s (2000) work, the models in this second specification are modeled after Osberg's (2000) empirical equations. The first model explored the relationship between % low income people (the incidence of poverty for people in private households) and variables such as

the unemployment rate, and import and export trade exposure. The remaining models in Specification #2 explore other important relationships with the poverty variable. The models in Specification #2 are:

$$POV_{it} = \beta_1 + \beta_2 FORDEP_{it} + \beta_3 MEDHINC_{it} + \beta_4 UNEMPR_{it} + \beta_5 TEIMP + \beta_6 TEEXP + \beta_7 DIV_{it} + \beta_8 PROVEMP_{it} + \beta_9 D_{1t} + \ldots + \beta_{18} D_{10t} + \mu_i + \epsilon_{it} \quad [24]$$

where POV = % low income of people living in private households, and TEIMP = % trade exposure to imports. The second and third models in this specification #2 are:

$$UNEMPR_{it} = \beta_1 + \beta_2 FORDEP_{it} + \beta_3 MEDHINC_{it} + \beta_4 POV_{it} + \beta_5 TEIMP_{it} + \beta_6 TEEXP_{it} + \beta_7 DIV_{it} + \beta_8 PROVEMP_{it} + \beta_9 D_{1t} + \ldots + \beta_{18} D_{10t} + \mu_i + \epsilon_{it} \quad [25]$$

$$MEDHINC_{it} = \beta_1 + \beta_2 FORDEP_{it} + \beta_3 UNEMPR_{it} + \beta_4 POV_{it} + \beta_5 TEIMP_{it} + \beta_6 TEEXP_{it} + \beta_7 DIV_{it} + \beta_8 PROVEMP_{it} + \beta_9 D_{1t} + \ldots + \beta_{18} D_{10t} + \mu_i + \epsilon_{it} \quad [26]$$

In addition, these three models in Specification #2 were estimated again with interaction terms between FORDEP and the new regional/provincial dummy variables.

5.2.1 Specification #3 (Approximation of Osberg (2000) logarithmic models)

Equation [24] and [26] were estimated a second time (as equations [27] and [28]) with a logarithmic specification of the unemployment rate. The results from these three specifications of models will be compared to those in Berck *et al* (2000) and Osberg (2000), as well as be examined to answer this study's central research questions.

All of the models were estimated as random effects panel data models with three time periods (census years). Thus, the individual differences between CSDs are considered to be random with β_1 representing the 'population mean intercept'. Random effects models are also called 'error components' models due to the fact that the error term consists of two components: ϵ_{it} (the overall disturbance term), and μ_i (the CSD specific error that reflects the individual differences across CSDs, but is constant over

time) (Griffiths *et al*, 1993). All of the models were estimated using the LIMDEP software package. [11]

5.3 Results and Discussion – Specification #1 (Approximation of Berck *et al* (2000) models)

The results from the models in Specification #1 (inspired by the Berck *et al* (2000) model) are shown in Table 2. A model specification test performed was the Lagrange Multiplier $\chi^2(1)$ test for error components. The null hypothesis is that individual error components do not exist; and thus, the classical regression would be a better model choice for estimation (Griffiths *et al*, 1993). The empirical results for this test show that the null hypothesis was rejected for every model in this specification. Thus, individual error components do exist in the model, justifying the use of the random effects panel procedure. This specification test was performed with every model in this study (across the three specifications) with the same result. Therefore, the use of random effects models (rather than classical regression models) was the correct choice for every estimation. F-tests were conducted on every model and suggested that all of the regressors' parameters were jointly significantly different from zero at the 99% level.

The first regression in specification #1 (equation [21]) examined the unemployment rate. From Table 2, it is evident that FORDEP has a positive and

[11] This study also tests the Kuznets hypothesis. This hypothesis is usually expressed in the context that a country's income inequality is low at low income levels, but will increase over time as a country's overall income level rises in conjunction with economic growth. Under this hypothesis, an inverted U-curve depicts the relationship between income distribution and the Gini coefficient (Li, Xie, and Zou, 2000). As a form of data verification, the existence of a Kuznets curve was tested with the three years of census data to see if it held with this particular dataset. The theory from the Li et al (2000) study is presented in Appendix B, along with the empirical models, and their corresponding results from the census data.

significant relationship with the unemployment rate.[12] This result means that CSDs with high degrees of forest dependence will suffer a high unemployment rate. Although this is somewhat surprising, it can be partially explained by the hypothesis that if a person lacks the skills to work in the forest industry in a highly forest dependent community, remaining employment opportunities may be low. This result may also be attributed to seasonal employment fluctuations common in the forest industry.

MEDHINC, income inequality (as represented by GINI), TEEXP, and DIV all have a negative and significant relationship with the unemployment rate. While the signs are as expected, the reader should be reminded that these results suggest that as the unemployment rate goes down, the Gini coefficient goes up (approaches one), which means that income inequality is increased. A possible explanation for this is if unemployment is high and those unemployed receive social assistance and unemployment insurance, more of the population would have equal incomes. However, if unemployment went down as more people became employed at diverse wages, it might be expected that income inequality would increase.

The negative relationships for the other variables coincide with general expected results. If unemployment goes down, more people are being employed, so it is natural for median household income to increase. As well, increased trade exposure to exports brings more income into a CSD, and increased economic diversity creates more employment opportunities. Therefore, it might also be expected that unemployment rates would decrease under these conditions. Also shown in Table 2 is the fact that aggregate demand (as represented by PROVEMP) does not have a significant effect on a CSD's

[12] Regression coefficients in all models are deemed significant at the 95% confidence level, unless otherwise stated.

unemployment rate. A possible explanation for this could be that the unemployed are not moving elsewhere to find employment; the mobility of citizens (or lack thereof) may not be highly correlated to employment opportunities. This result is contrary to Berck *et al*'s (2000) finding that there was a long run relationship between state employment levels and county levels of unemployment.

The only provincial dummy variable in the equation [21] regression that is not significant is Alberta. The coefficients on the rest of the dummy variables mean that only Manitoba and Saskatchewan report unemployment rates lower than those in Ontario. The rest of the geographic areas report higher unemployment rates than Ontario from 1986-1996, with Newfoundland having a 25.34% higher rate. These latter results could be attributed to the historically depressed economies in the Maritimes. The fact that Alberta and Ontario are not significantly different from each other may be due to their strong economies over the study period. This model, equation [21], has an adjusted R^2 of 52.4%.

The dependent variable in equation [22] is MEDHINC. The results in Table 2 show that forest dependence does not have a significant relationship with the median household income of a CSD. UNEMPR and GINI both have negative and significant relationships with MEDHINC. Thus, as the unemployment rate decreases and income inequality decreases (Gini coefficient approaches zero), median household income increases. Increases in DIV and PROVEMP have a significant, positive effect on median household income. This positive effect was expected for both variables. On the other hand, since a CSD's total employment is included in the measure of aggregate demand, if a CSD's total employment increased, it might be responsible for the increase in median

household income. All of the dummy variables in this regression are significant and positive which indicate that CSDs in each province or territory in Canada (excluding Yukon) have higher median household incomes than CSDs in Ontario. However, Quebec CSDs have the lowest difference from Ontario; their median household incomes are only marginally higher than those in Ontario.

Equation [23], the last model in Specification #1, explores the relationship between the Gini coefficient and other variables. From Table 2, it is evident that a CSD's forest dependence and economic diversity do not play a significant role in determining income inequality. Thus, the composition of the economy does not seem to be a significant factor in how the households are distributed over the income classes of a CSD. Attributing factors that are more plausible include UNEMPR and MEDHINC, whose significant relationships with the Gini coefficient have already been described. However, MEDHINC and UNEMPR are significant and negative in this regression. These results suggest that increases in median household income and the unemployment rate lead to greater income equality.

The regression results also suggest that aggregate demand (represented by PROVEMP) plays a significant role in determining income inequality. However, as PROVEMP increases, income inequality increases. This suggests that as the provincial economy fares better, there is an increasingly unequal distribution of the earned income in CSDs. All of the dummy variables are significant and their signs all indicate that every area has higher Gini coefficients (higher income inequality) than the Gini coefficients found in Ontario. Even though most of the variables were significant, this

model's adjusted R^2 value is low with only 11.5% of the variation in the Gini coefficient explained by the regressors.

For the alternate specification for each of the three models, the interaction terms were simply added to the original models. As seen in Table 2, the signs and significance for all of the common variables' parameters are the same with only very small changes to their numerical values.

In regression [21] with interaction terms, the relationship between UNEMPR and each interaction term can be interpreted with all other variables held constant. FORDEP now represents forest dependence in Ontario (the excluded provincial dummy variable). In Table 2, the parameter for FDBC is negative and significant. Thus, the relationship between FORDEP and UNEMPR is weaker in BC than in Ontario. Furthermore, the combination of the parameters for FORDEP and FDBC results in an actual parameter that is close to zero for FDBC. Thus, this suggests that as forest dependence increases in BC, there is little response in the unemployment rate. There must be some structural differences in the economy of CSDs in BC that differentiate this province from the others. In contrast, the positive relationship between FORDEP and UNEMPR is significantly larger in PRAIR, QUE, and MARI than in Ontario. The lack of significance on the FDNWT interaction term can be interpreted that the relationship between FORDEP and UNEMPR is similar to the same effect in Ontario.

In regressions [22] and [23] without interaction terms, there was no significant relationship between FORDEP and MEDHINC or between FORDEP and GINI. Running these two models again with the interaction terms produced the same result. This holds true for each of the regional/provincial dummy variables.

Table 2: Parameter Estimates (Standard Error) from Specification #1 (Approximation of Berck *et al* (2000) Framework) for Census Data 1986-1996

	Dependent Variable					
Independent Variables	UNEMPR = [21]		MEDHINC† = [22]		GINI = [23]	
	w/o interactions	w/interactions	w/o interactions	w/interactions	w/o interactions	w/interactions
Intercept	24.919**	25.357**	2.269**	2.285**	0.379**	0.378**
	(1.569)	(1.578)	(0.143)	(0.144)	(0.0127)	-0.0127
FORDEP	0.0968**	0.0620**	-0.000581	-0.0000954	-0.0000307	0.0000341
	(0.00559)	(0.0139)	(0.000524)	(0.00132)	(0.0000414)	(0.000101)
MEDHINC†	-2.706**	-2.706**			-0.0253**	-0.0253**
	(0.0980)	(0.0977)			(0.000718)	(0.000719)
UNEMPR			-0.0207**	-0.0206**	-0.000504**	-0.000509**
			(0.000799)	(0.000799)	(0.0000717)	(0.0000720)
GINI	-3.673**	-3.725**	-1.800**	-1.801**		
	(0.928)	(0.930)	(0.0809)	(0.0808)		
TEEXP	-0.157**	-0.162**				
	(0.0138)	(0.0138)				
DIV	-1.114**	-1.222**	0.0731**	0.0674**	0.00133	0.00113
	(0.241)	(0.241)	(0.0215)	(0.0216)	(0.00175)	(0.00177)
PROVEMP†	-0.000490	-0.000251	0.00425**	0.00424**	0.000128**	0.000128**
	(0.00278)	(0.00278)	(0.000250)	(0.000250)	(0.0000226)	(0.0000226)
NFLD	25.339**	25.030**	1.732**	1.723**	0.0510**	0.0515**
	(1.441)	(1.452)	(0.133)	(0.134)	(0.0116)	(0.0117)
PEI	4.583**	4.410**	1.715**	1.710**	0.0533**	0.0539**
	(1.596)	(1.600)	(0.148)	(0.149)	(0.0124)	(0.0124)
NS	4.511**	4.159**	1.416**	1.409**	0.0674**	0.0678**
	(1.512)	(1.522)	(0.141)	(0.142)	(0.0116)	(0.0117)
NB	7.0319**	6.572**	1.539**	1.529**	0.0555**	0.0558**
	(1.427)	(1.446)	(0.131)	(0.133)	(0.0113)	(0.0114)
QUE	4.395**	3.901**	0.354**	0.371**	0.0201**	0.0208**
	(0.603)	(0.619)	(0.0562)	(0.0580)	(0.00463)	(0.00473)
MB	-2.948**	-3.241**	0.978**	0.962**	0.0546**	0.0551**
	(1.371)	(1.379)	(0.126)	(0.128)	(0.0109)	(0.0109)
SK	-3.999**	-4.251**	1.185**	1.172**	0.0609**	0.0613**
	(1.352)	(1.360)	(0.124)	(0.125)	(0.0109)	(0.0109)
AB	-0.975	-1.252	1.249**	1.236**	0.0503**	0.0508**
	(1.157)	(1.164)	(0.107)	(0.108)	(0.00904)	(0.00909)
BC	3.183**	4.976**	1.514**	1.492**	0.0518**	0.0549**
	(1.0917)	(1.159)	(0.101)	(0.108)	(0.00847)	(0.00885)
NWT	10.057**	9.922**	2.170**	2.161**	0.0781**	0.0725**
	(1.777)	(1.801)	(0.168)	(0.171)	(0.0133)	(0.0135)
FDBC		-0.0431**		0.000338		-0.000165
		(0.0199)		(0.00190)		(0.000141)
FDPRAIR		0.0788**		0.00345		-0.0000291
		(0.0237)		(0.00220)		(0.000183)
FDQUE		0.0594**		-0.00196		-0.0000760
		(0.0162)		(0.00153)		(0.000118)
FDMARI		0.0574**		-0.0000528		-0.0000369
		(0.0190)		(0.00180)		(0.000139)
FDNWT		0.0184		0.00111		0.00237**
		(0.115)		(0.0104)		(0.000969)
# of Observations	12606	12606	12606	12606	12606	12606
Adjusted R^2	0.524	0.530	0.331	0.332	0.115	0.115
F-test	868.28	677.39	415.86	313.84	109.98	82.91
LM-test (prob value)	3375.79 (.0000)	3243.32 (.0000)	4680.26 (.0000)	4668.53 (.0000)	60.94 (.0000)	60.70 (.0000)
**P<0.05	*P<0.10					
† MEDHINC and PROVEMP have been scaled (raw values /10,000)						

5.4 Results and Discussion – Specification #2 (Approximation of Osberg (2000) linear models)

The models in Specification #2 explored the relationships that exist between many of same variables in Specification #1 with the addition of an incidence of poverty variable, POV. The first regression, specified in equation [24], has POV as its dependent variable. The parameter estimates are shown in Table 3. FORDEP, TEEXP, and DIV all have positive and significant relationships to POV. Thus, the incidence of poverty for people in private households increases as these variables increase. Since a positive relationship has already been established between forest dependence and the unemployment rate, this negative relationship between forest dependence and the incidence of poverty is probably not surprising. For example, the seasonal nature of forestry or other structural issues associated with forestry activity may partially explain this relationship. However, this negative relationship between forest dependence and poverty suggests high rates of poverty in private households in highly forest dependent CSDs. On the other hand, how does trade exposure to exports and economic diversity affect poverty? High values of these attributes are usually encouraged, as they are thought to enhance the stability of the entire community. Since the Statistics Canada measurement of POV already accounts for CSD size and family composition, further research may be necessary to examine how increased trade exposure to exports and economic diversity contribute to an increase in the percentage of low income people in private households.

Other results from this model outline negative and significant relationships of MEDHINC, UNEMPR, and TEIMP to POV. These results indicate that increases in these three regressors would cause decreases in the number of low income people in

private households. This finding for MEDHINC is intuitive. As well, the relationship of TEIMP to POV might have been expected. Increasing trade exposure to imports makes a CSD reliable on outside sources for different products and services. If this includes housing materials, some food, and clothing, these products may have a price premium reflecting their internal scarcity in the CSD. In turn, this would drive up the share of household income spent on necessities, thereby pushing more people into the low income bracket.

The negative relationship between UNEMPR and POV is a more complex, however. It could be hypothesized that the unemployed are receiving enough money from unemployment insurance and other social assistance sources so that they do not fall into the low income bracket. On the other hand, if a person becomes employed, working only a few hours a week or in a low wage job, she may fare worse and fall below the poverty line. The negative and significant coefficient on PROVEMP also shows that increases in this variable would lead to decreases in POV.

Quebec is a province in this regression whose provincial dummy coefficient is not significant (and Newfoundland is significant at a 90% confidence level). The results from the other dummy variables show that all the other areas experience lower percentages of people deemed low income than the incidence of poverty in private households in Ontario. For example, the incidence of poverty in Prince Edward Island and the Northwest Territories are 11.4% and 21.4% lower, respectively, than the rates in Ontario.

The addition of POV in regression [24] allows the results to be compared to more of Berck *et al*'s (2000) work. Even though the variables in Berck *et al* (2000) differ

slightly from the variables used in the present study, but it might be useful to determine if common relationships can be identified for the general poverty variable. Berck *et al* (2000) found mixed or little evidence that decreases in timber-related employment were associated with increases in poverty program participation. In regression [24], a positive and highly significant relationship was found to exist between FORDEP and POV. However, both studies did show that a significant negative relationship exists between aggregate demand and poverty.

Some of the results in this regression can also be compared to the work in Osberg (2000). Contrary to the results seen in the present study, Osberg (2000) found no significant relationship between either of the trade exposure variables and poverty intensity. As well, Osberg's (2000) regression showed that a positive and significant relationship existed between the poverty intensity and the unemployment rate. The regression results for equation [24] report a negative and significant relationship between UNEMPR and POV, as well as significant relationships for both of the trade exposure variables (Table 3). This discrepancy could be due to the different datasets used. Whereas Osberg (2000) used country-level data and a general poverty intensity variable, Canadian CSD-level data was used here with an incidence of poverty variable for a specific group of people.

The next regression in Specification #2 examined the unemployment rate (making it similar to regression [21]). However, POV replaced the Gini coefficient and the TEIMP variable was added (Table 3). The results between these two regressions are robust for the common variables (and they have similar adjusted R^2 values of approximately 52%). Forest dependence is still positively and significantly related to the

unemployment rate. As well, MEDHINC, TEEXP, DIV and PROVEMP have negative and significant relationships with the unemployment rate that hold in both regressions.

Other results from this regression show that POV has a negative and significant relationship with UNEMPR. Thus, as the unemployment rate increases in a CSD, the incidence of poverty tends to decrease. This is the same result seen in regression [24]. The dummy variable signs and coefficients differ slightly from those seen in regression [21]. In Table 3, the results for the new regression show that every dummy variable is significant and there are slight changes in the magnitude (but not the sign) of their coefficients. Manitoba, Saskatchewan, and Alberta all experience lower unemployment rates than Ontario, while the other areas report higher unemployment rates when compared Ontario.

Looking at the specifications of equations [22] and [26] that share the same differences as [21] and [25], the robustness of the shared variables can be tested again while exploring some new relationships. This can be done by comparing the parameter estimates in Tables 2 and 3 for the variables shared between the two regressions. The dependent variable in both regressions is MEDHINC. In regression [26], the parameters for FORDEP, UNEMPR, DIV and PROVEMP remain robust (Table 3). Forest dependence is not significant to median household income, while the unemployment rate has a negative and significant effect on the dependent variable. As well, economic diversity and aggregate demand are positive and significantly related to a CSD's median household income. Additional results in regression [26] show that POV is significant and negatively related to MEDHINC. This result is the same as those found in regressions [24] and [27].

Some new results found in regression [26] are that while both trade exposure variables are significant, TEIMP is negative and TEEXP is positive in their relationships to MEDHINC. Thus, trade exposure to exports is seen to increase median household income, while trade exposure to imports seems to be related to decreases in this income variable. If a CSD is relying on outside sources for products, it is reasonable to think that they lack the potential to create them themselves. It might then be found that particular communities only have a few, low wage industries like the service sector. This would keep the median household income low. All of the dummy variables are significant in this regression. As well, their coefficients show that all of the areas have higher median household incomes than those found in Ontario. This is the same result seen in regression [22].

As expected, once the three models in Specification #2 were run with provincial interaction terms, the parameter signs did not change (compared to the original models), and there was very little change in their significance and numerical values. One important change noted in regression [24] with interaction terms is that the positive relationship between FORDEP and POV in Ontario was significant at the 90% level (instead of the 95% level seen in [24] without interaction terms). Also, in regression [24] in Table 2, the parameter for FORDEP is small. Thus, the effect from the positive and significant relationship between FORDEP and POV is not very strong for Ontario. In addition, the parameters for BC, PRAIR, MARI and NWT suggest that these regions/provinces are not significantly different from Ontario in terms of the effect of the positive relationship between FORDEP and POV. The parameter for FDQUE shows that the results are marginally different from those seen in Ontario.

Since the specification of regression [25] is so similar to regression [21], the outcome when regression [25] was run with interaction terms was the same as regression [21] with interaction terms. Thus, the effect of a positive (and significant) relationship between FORDEP and UNEMPR is weaker in BC than the same effect in Ontario. As well, the effect of the positive relationship between FORDEP and UNEMPR is larger in PRAIR, QUE, and MARI than the same effect in Ontario. The FDNWT interaction term was not significant, therefore the effect of the positive and significant relationship between FORDEP and UNEMPR is similar to the same effect in Ontario.

The lack of significance between FORDEP and MEDHINC found originally in regression [22] held in regression [26] with interaction terms.

Table 3: Parameter Estimates (Standard Error) for Specification #2 (Approximation of Osberg (2000) Framework) for Census Data 1986-1996

	Dependent Variable					
Independent Variables	POV = [24]		UNEMPR = [25]		MEDHINC† = [26]	
	w/o interactions	w/interactions	w/o interactions	w/interactions	w/o interactions	w/interactions
Intercept	36.146**	36.089**	25.645**	26.130**	2.622**	2.636**
	(1.515)	(1.525)	(1.574)	(1.581)	(0.127)	(0.128)
FORDEP	0.0381**	0.0232*	0.101**	0.0654**	-0.0000626	-0.000489
	(0.00562)	(0.0136)	(0.00574)	(0.0140)	(0.000484)	(0.00119)
MEDHINC†	-5.081**	-5.072**	-2.886**	-2.891**		
	(0.0952)	(0.0952)	(0.106)	(0.105)		
UNEMPR	-0.0502**	-0.0507**			-0.0147**	-0.0146**
	(0.00873)	(0.00875)			(0.000713)	(0.000714)
POV			-0.0496**	-0.0512**	-0.0350**	-0.0350**
			(0.00920)	(0.00919)	(0.000668)	(0.000668)
TEIMP	-0.182**	-0.180**	-0.0506	-0.0564*	-0.0161**	-0.0160**
	(0.0313)	(0.0313)	(0.0322)	(0.0322)	(0.00264)	(0.00264)
TEEXP	0.256**	0.255**	-0.117**	-0.118**	0.0316**	0.0316**
	(0.0268)	(0.0268)	(0.0276)	(0.0275)	(0.00222)	(0.00222)
DIV	1.675**	1.732**	-1.044**	-1.151**	0.178**	0.176**
	(0.234)	(0.235)	(0.241)	(0.242)	(0.0198)	(0.0199)
PROVEMP†	-0.0192**	-0.0192**	-0.00208	-0.00185	0.00215**	0.00214**
	(0.00270)	(0.00271)	(0.00278)	(0.00278)	(0.000223)	(0.000224)
Nfld	-2.762*	-2.871**	24.873**	24.561**	0.897**	0.883**
	(1.416)	(1.427)	(1.439)	(1.448)	(0.120)	(0.121)
PEI	-11.346**	-11.449**	3.658**	3.462**	0.649**	0.638**
	(1.543)	(1.551)	(1.594)	(1.597)	(0.135)	(0.136)
NS	-8.546**	-8.700**	3.734**	3.374**	0.497**	0.485**
	(1.461)	(1.474)	(1.508)	(1.518)	(0.128)	(0.130)
NB	-6.476**	-6.647**	6.388**	5.925**	0.676**	0.662**
	(1.384)	(1.406)	(1.424)	(1.443)	(0.118)	(0.120)
QUE	-0.512	-0.768	4.254**	3.742**	0.103**	0.103*
	(0.584)	(0.601)	(0.601)	(0.617)	(0.0512)	(0.0529)
MB	-10.091**	-10.046**	-3.868**	-4.189**	0.127	0.112
	(1.330)	(1.340)	(1.371)	(1.378)	(0.114)	(0.115)
SK	-8.870**	-8.861**	-4.939**	-5.228**	0.299**	0.286**
	(1.317)	(1.326)	(1.356)	(1.363)	(0.111)	(0.112)
AB	-8.289**	-8.262**	-1.767	-2.074*	0.428**	0.415**
	(1.121)	(1.131)	(1.157)	(1.165)	(0.0968)	(0.0979)
BC	-6.791**	-6.767**	2.547**	4.334**	0.761**	0.725**
	(1.055)	(1.123)	(1.089)	(1.156)	(0.0917)	(0.0984)
NWT	-21.413**	-21.283**	8.483**	8.332**	0.707**	0.701**
	(1.713)	(1.744)	(1.782)	(1.805)	(0.155)	(0.158)
FDBC		0.00981		-0.0423**		0.00155
		(0.0193)		(0.0198)		(0.00171)
FDPRAIR		-0.0264		0.0793**		0.00164
		(0.0230)		(0.0236)		(0.00195)
FDQUE		0.0287*		0.0618**		-0.000107
		(0.0157)		(0.0162)		(0.00137)
FDMARI		0.0199		0.0582**		0.000580
		(0.0185)		(0.0190)		(0.00161)
FDNWT		-0.0654		0.00716		-0.00176
		(0.112)		(0.115)		(0.00911)
# of Observations	12606	12606	12606	12606	12606	12606
Adjusted R^2	0.304	0.304	0.528	0.534	0.416	0.416
F-test	324.12	251.80	829.35	656.54	529.19	409.88
LM-test (prob. value)	2997.38 (.0000)	2981.21 (.0000)	3296.74 (.0000)	3158.65 (.0000)	5746.84 (.0000)	5736.28 (.0000)
**P<0.05	*P<0.1					
† MEDHINC and PROVEMP have been scaled (raw values /10,000)						

5.5 Results and Discussion – Specification #3 (Approximation of Osberg (2000) logarithmic models)

Following the work in Osberg (2000), a logarithmic specification for the unemployment rate was employed to see if this change in specification would affect the results. As seen in Table 4, the specifications shows that the coefficients signs', magnitude, and significance changed very little from the results in Table 3. The adjusted R^2 values for both the linear and logarithmic regressions were both approximately 30%. As well, the logarithmic form of the unemployment rate is still negative and significant in its relationship to the incidence of poverty in private households. These results are comparable to Osberg's (2000) work - changing the model to contain a logarithmic form of unemployment did little to alter the results found in the linear model.

Regression [28] in Specification #3 again tests whether the results are subject to change if the functional form of unemployment changes. Table 4 shows that the logarithmic form of the unemployment rate makes little difference for the signs, significance, and magnitude of the coefficients. As well, the adjusted R^2 value of 40.9% differs little from the adjusted R^2 value of 41.6% in regression [26]. Two slight changes among the dummy variables are that the median household income in Manitoba is no longer significantly different from those found in Ontario, and Quebec's significance drops from the 95% to the 90% confidence level.

Table 4: Parameter Estimates (Standard Error) for Specification #3 (Approximation of Osberg (2000) Framework) for Census Data 1986-1996

	Dependent Variable	
Independent Variables	POV = [27]	MEDHINC† = [28]
Intercept	35.847**	2.700**
	(1.530)	(0.130)
FORDEP	0.0359**	-0.000451
	(0.00561)	(0.000491)
MEDHINC†	-5.014**	
	(0.0947)	
UNEMPR		
Log(UNEMPR)	-0.410**	-0.157**
	(0.112)	(0.00916)
POV		-0.0352**
		(0.000682)
TEIMP	-0.174**	-0.0134**
	(0.0314)	(0.00269)
TEEXP	0.255**	0.0305**
	(0.0269)	(0.00227)
DIV	1.805**	0.216**
	(0.234)	(0.0202)
PROVEMP†	-0.0190**	0.00217**
	(0.00271)	(0.000228)
Nfld	-3.408**	0.735**
	(1.409)	(0.121)
PEI	-11.290**	0.666**
	(1.546)	(0.137)
NS	-8.519**	0.502**
	(1.462)	(0.130)
NB	-6.523**	0.664**
	(1.387)	(0.120)
QUE	-0.541	0.0976*
	(0.585)	(0.0520)
MB	-10.026**	0.106
	(1.333)	(0.116)
SK	-8.807**	0.274**
	(1.321)	(0.113)
AB	-8.227**	0.428**
	(1.123)	(0.0984)
BC	-8.771**	0.770**
	(1.057)	(0.0931)
NWT	-21.493**	0.696**
	(1.715)	(0.157)
Number of Observations	12606	12606
Adjusted R^2	0.303	0.409
F-test	323.89	513.15
LM-test (prob. value)	2941.00 (.0000)	5529.50 (.0000)
**P<0.05		
† MEDHINC and PROVEMP have been scaled (raw values /10,000)		

5.6 Chapter Summary and Further Discussions

The models estimated in this study help to answer some of the central research questions such as: how does the forest dependence of a CSD affect indicators of economic performance? The results from the random effects regressions showed that forest dependence was positively and significantly related to a CSD's unemployment rate and to the incidence of poverty for people in private households. Thus, highly forest dependent CSDs will suffer with high rates of unemployment and poverty. This emphasizes the need for economic diversification in order to increase the well-being of its residents.

Median household income and the Gini coefficient of a community are not significantly affected by its degree of forest dependence. It is surprising that the two important income-related variables used in this study are not affected by the share of forestry activity in a CSD. Even though some CSDs' unemployment rates and incidence of poverty in private households may be high and can be attributed to the high degree of forest dependence, the values of their median household income and Gini coefficient are not directly affected by the economic activity in the forestry sectors. These relationships between forest dependence and the unemployment rate, median household income, the Gini coefficient, and the incidence of poverty were robust across all specifications.

Much of this study centered on how the degree of forest dependence in a CSD affected other economic indicators. Hence, once forest dependence was calculated, it acted as an exogenous variable. This is the ideal treatment, as forest dependence is not believed to act as a good indicator in and of itself. Assessments of economic sustainability become more valuable when they examine indicators in relation to forest

dependence. In this study, different models were examined to see how other variables reacted to the degree of forest dependence. However, how and why is a particular CSD as forest dependent as it is? Most researchers would agree that if the people and the industries in a CSD have the necessary resources and technology, the growth of the forest industry and forest-related sectors is natural. However, some of the findings in this study suggest that high degrees of forest dependence are not sustainable. Policy outcomes that might ensue could be to try to decrease a CSD's reliance on the forest industry and coincidentally diversify the CSD's economy into new areas. This is an ideal concept, but perhaps forest dependence is more closely tied to a CSD's available opportunities. More specifically, is forest dependence higher in more northern or remote communities due to the lack of resources and/or technology to further diversify? Perhaps the forest sector is a vital support system as the population's main income and employment source. If this is the case, decreasing a CSD's reliance on the forest industry may be more difficult than first imagined or may not be desirable at all. For example, a forced decrease in forest dependence may come at the expense of skilled forestry workers who may fall from full-time to part-time, or lose their jobs altogether. Hence, it may be difficult to generate positive change in indicators such as the unemployment rate and the incidence of poverty that seem to be closely tied to the degree of forest dependence. The reasons behind the degree of forest dependence in a CSD and whether diversification is the desirable policy outcome both deserve future study.

The third central research question was: How do other variables such as economic diversity, trade exposure, and aggregate demand affect indicators at the CSD level? These interesting relationships were also uncovered in the three sets of models. For

instance, MEDHINC, GINI, TEEXP, DIV, and POV were all negatively and significantly related to a CSD's unemployment rate. These results were robust across all applicable specifications. As well, MEDHINC was significantly affected by GINI, TEIMP, POV, DIV, and TEEXP. However, the former three variables had negative relationships, while the latter had positive relationships with MEDHINC. Again all of these results remained robust across specifications. There was no significant relationship in any model between the Gini coefficient and the level of economic diversity. In regards to POV, MEDHINC, UNEMPR, and TEIMP all had negative and significant relationships with this variable. TEEXP and DIV were found to be positive and significantly related to POV. These results were found to hold true across specifications.

Aggregate demand (PROVEMP) was found to have a significant relationship with three variables: MEDHINC, GINI, and POV. The latter variable had a negative relationship with PROVEMP, while the other two variables had positive relationships. The unemployment rate of a CSD was not significantly affected by PROVEMP in any of the models.

Even though some of the models were estimated with changes to their functional form, changing the specifications from linear to logarithmic made little difference to the original results.

Including the dummy variables in each model enabled comparisons between provinces and the Northwest Territories with respect to four key variables. With the unemployment rate as the dependent variable, both models showed that the CSDs in Manitoba and Saskatchewan experience lower unemployment rates than those in Ontario (the excluded dummy variable), with everything else held constant. The rest of the

geographic aggregates (with the exception of Alberta) had significantly higher rates of unemployment than in Ontario. All of the provinces and one territory were significant in the models of median household income. In addition, all areas reported higher median household incomes than those among CSDs in Ontario. A similar result was seen in models with the Gini coefficient as the dependent variable. All areas were significant and showed higher Gini values than those seen in Ontario. A robust outcome was also seen among the dummy variables in the incidence of poverty models. All significant provinces and territory had lower percentages of low income people in private households than in Ontario (all else held constant). These results for the provincial dummy variables remained robust across specifications.

Additional models were estimated in order to test the influence of the key findings relating to high forest dependence at a regional/provincial level. Although the other models showed a general consensus that higher levels of forest dependence cause higher unemployment and a higher incidence of poverty, the influence from the former relationship is variable at the regional/provincial level. Specifically, the positive relationship between forest dependence and the unemployment rate is weakest (almost nonexistent) in British Columbia, yet very strong in the Prairies, Maritimes, and Quebec when all regional/provincial dummy variables are compared to Ontario. Thus, these alternate specifications with interaction terms allow for the ranking of the relative importance of the relationship between forest dependence and unemployment at the regional/provincial level.

The same models explaining the incidence of poverty with interaction terms between forest dependence and the provinces not only showed that this relationship is

weak at the regional/provincial level, but that the effects of this relationship are approximately uniform across the regions/provinces. The exception was Quebec, which showed a marginal difference for the effect of the relationship between forest dependence and poverty from the rest of Canada. Thus, the interaction models suggest that from a policy perspective, the effect that increasing forest dependence has on the unemployment rate is much more worrisome than its effect on the incidence of poverty in private households.

6 CONCLUSION

There are many operational definitions used for sustainability and the assessment of sustainability of an area depends on which definition is employed and the criteria used for measurement. Although groups worldwide have tried to set sustainable development goals, there has been less effort in the selection and design of economic sustainability indicators. This is unfortunate, as the use of indicators can provide policy-makers with guidance and a measure for tracking sustainable development. Good economic sustainability indicators are normative, consistent with theoretical concepts of well-being or 'economic welfare', and be able to be linked to management or policy options. As well, indicators should be able to be predicted or forecasted, measurable at relatively low cost, and reliable such that repeated measurement of the same indicator achieve the same quantitative result. Many of these properties could be attributed to the indicators in the national census.

6.1 Assessment of Study's Indicators

This study used indicators such as median household income, the incidence of poverty in private households, and the unemployment rate that were extracted directly from the Canadian national census. However, the study was not limited to the use of census data. A combination of census data and outside data sources were used to construct the forest dependence index, the Gini coefficient, the trade exposure variables, a measure of economic diversity, and aggregate demand. Economic diversity was included as an indicator as a 'check' of the data; it was always included with the forest

dependence index. This entire suite of indicators was carefully chosen to include the most widely used and respected indicators in the field of economic sustainability. The indicators were also chosen to approximate influential work examining economic indicators by Berck *et al* (2000) and Osberg (2000). Berck *et al* (2000) focused on indicators such as unemployment, poverty, and aggregate demand in the context of timber-related employment. Osberg (2000) used the unemployment rate and trade exposure to determine the impacts on a poverty variable. Consequently, this study's choice of indicators uncovered many important relationships between forest dependence and the indicators and among the indicators themselves. These relationships help define economic sustainability for many CSDs across Canada. As well, the results suggest that the potential exists for these relationships to guide future policy decisions.

In retrospect, it might have been more beneficial to have included a poverty variable that was more representative of the entire CSD. The incidence of poverty indicator in this study was measured with respect to only the private households in the CSD. Hence, it is difficult to portray the true amount of poverty that exists within the entire CSD, or in different groups of people. Besides this suggested change, the study could have also benefited from the inclusion of other variables. This issue is addressed in section 6.3.

6.2 Study Summary

The examination of these community level economic sustainability indicators using the 1986, 1991, and 1996 census' did provide valuable information as to how

various social and economic factors are related to forest dependence. As well, this study also uncovered relationships that showed up among the indicators.

Although some of the descriptive graphs in Chapter 4 did not depict clear trends, the correlation analysis did hint at possible relationships between various indicators and forest dependence. An increase in a CSD's forest dependence was found to be negatively correlated to its median household income, incidence of low income for people living in private households, and the unemployment rate. In the correlation analysis, the Gini coefficient values were not related to the degree of forest dependence. Increased forest dependence was also correlated to decreases in the CSDs' economic diversity and increases in its trade exposure to the export market. When non-forest dependent CSDs were added to examine their differences, especially in relation to the group of CSDs that were more than 50% forest dependent, there were some interesting results. The non-forest dependent CSDs had slightly lower median household incomes, lower unemployment, lower poverty (incidence of low income), lower dependence on trade exposure to exports and higher diversity.

Chapter 5 examined the estimation of various empirical models in efforts to further characterize the relationships between forest dependence and other indicators. An important conclusion arising from the literature's conceptual analysis was that forest dependence is best incorporated into sustainability assessments as an exogenous variable. In doing so, the relationships between indicators are best defined in a forest dependence context. This information was incorporated into the present study.

Two important findings were uncovered in this study. The initial national level models show that highly forest dependent CSDs will most likely suffer from high rates of

unemployment and poverty (holding all other variables constant). These results suggest that high degrees of forest dependence may leave the CSD's economy vulnerable to outside economic shocks and slow to rebound from sudden sectoral changes in employment. This might prove detrimental to the residents of those communities who must deal with the income, employment and poverty changes that can ensue. These relationships (between FORDEP and POV and FORDEP and UNEMPR) could be attributed to the structure of forest industry jobs or the possibility that the forest dependence index is picking up 'northern' characteristics. For example, as you move north in any province, the probability of finding highly forest dependent CSDs may increase due to the lack of resources in these towns to develop widely diverse economies. Also, there may be aspects relating to aboriginal communities that affect the unemployment rate and poverty variables that are not captured in this database. Areas with lower levels of forest dependence fared better enough in this study to hint at an economic plan of diversification for CSDs in the high forest dependence categories. However, as discussed in chapter 5, caution must be exercised when implementation diversification plans for some CSDs.

The model estimation suggested that indicators such as trade exposure and aggregate demand were significantly related to other economic indicators. Median household income, the Gini coefficient, trade exposure to exports, economic diversity, and the incidence of poverty in private households were all negatively and significantly related to a CSD's unemployment rate. As well, median household income had significant relationships with the Gini coefficient, trade exposure to imports, the incidence of poverty, economic diversity, and trade exposure to exports. However, the

former three variables had negative relationships, while the latter two had positive relationships with median household income. There was no significant relationship in any model between the Gini coefficient and the level of economic diversity. In regards to the incidence of poverty in private households, median household income, the unemployment rate, and the trade exposure to imports all had negative and significant relationships with this variable. Trade exposure to exports and economic diversity were found to be positive and significantly related to the incidence of poverty variable.

Aggregate demand was found to have a positive and significant relationship with median household income and the Gini coefficient, and a negative and significant relationship with the incidence of poverty in private households.

Regarding the provincial dummy variables and the unemployment rate, the models showed that, with all else held constant, the CSDs in Manitoba and Saskatchewan experience lower unemployment rates than those in Ontario. The rest of the geographic areas (with the exception of Alberta) had higher rates of unemployment than in Ontario. Also found was the fact that all of the provinces and one territory reported higher median household incomes than those among CSDs in Ontario. Similarly in another model, all areas were significant and showed higher Gini values than those seen in Ontario. A robust outcome was also seen in the incidence of poverty models; all provinces and one territory had lower percentages of low income people in private households than in Ontario.

Additional models with interaction terms at the regional/provincial level showed that the positive relationship between forest dependence and the unemployment rate was weakest in British Columbia, and very strong in the Prairies, Maritimes, and Quebec. In

contrast, the effect of the positive relationship between forest dependence and the incidence of poverty was relatively weak and uniform across Canada.

While the results in this study outline some important relationships that exist between indicators at the CSD level, further research and continued exploration of the census data will further enhance our understanding of these relationships across time.

6.3 Limitations of the Study and Future Research Possibilities

The Canadian National Census provided a solid basis for studying the behavior of some economic sustainability indicators across a subset of CSDs over the period of 1986-1996. In fact, the census is the only standardized survey in Canada that is big enough to generate indicators at the community level such that comparisons can be made between CSDs across the country. As well, the indicators were examined using the context of the whole CSD, rather than examining indicators reflective of one sector of the economy. As mentioned in Chapter 2, this proves to be vital in the proper assessment of sustainability. The subtle interactions between the various sectors of a local and provincial economy all contribute to an indicator's behaviour. Thus, an economy-wide perspective rather than a sector-specific perspective is important. This also alludes to the fact that a single sector should not be fully responsible for achieving sustainability when other agents (in other sectors) are also influencing economic conditions across sectors.

Although the three years of census data provided a glimpse of indicator trends through time, it would be ideal to continue the same analysis as new years of census data become available. With the same attention to detail as found in this study, new data can be manipulated to add to the original comprehensive, standardized database. By

continually updating the database and monitoring for changes in sustainability and indicator definitions, it may be possible to examine economic sustainability for most CSDs in Canada over long periods of time. Another future endeavor that would enhance this database would be to work with Statistics Canada to fill in the information gaps that prevent some CSDs from being included in the final database, for example many small communities. This could create a more complete picture of economic sustainability in CSDs of all sizes. If it was deemed necessary, further work could also refine some of the data sources used in this study. For example, two different data sources were used to produce the average income by industry estimates.

This study confirms that the Canadian National Census contains useful indicators. These indicators should be included in all future assessments of the sustainability of CSDs in Canada. An excellent starting point would be to incorporate the indicators used in this study into the CCFM framework. Since this policy document guides the implementation and measurement of SFM in Canada, the inclusion of such indicators is a necessary step to maintaining the credibility of the framework. As well, it would produce more accurate assessments of the economic sustainability of an area. Given the comprehensive database created for this study, more attention can be given to economic sustainability indicators and they can be incorporated in community level and regional level sustainability assessments.

It would also be valuable if the database used in this study could be expanded to include other variables, including some measure of "augmented income" that would include the value of non-market goods and services. This modification may be especially useful for some rural and aboriginal communities where subsistence hunting and other

non-market activities may comprise a large portion of their 'income and employment'. As such, these communities are examples of where residents may highly value environmental amenities with a low concern for traditional income sources. With no way to capture these environmental values in the present database, the reported indicators may not give an accurate picture of the sustainability in these types of communities. Although results from this study suggest plans for diversification for highly forest dependent communities, the exclusion of non-market sources of income may mask the true diversity of the economy in some CSDs. Thus, it may be wise to avoid aggressive attempts to diversify some communities until the income indicators can reflect both traditional and non-traditional income sources. Although these augmented income data may not exist at the CSD level, perhaps procedures in the future would permit this inclusion at the regional level. This would greatly enhance the credibility of the income category in the assessment of sustainability at regional and community levels.

In addition, although the distributional component of sustainable development (see section 2.1.1) was captured quite well in this study, analysis of the growth component suffered by not being able to account for income in terms of augmented sources such as non-market activities and depletion and degradation of environmental stocks and services.

Another valuable extension of the database would be the inclusion of social indicators. As mentioned in Chapter 2, social indicators supplement economic indicators to provide a more complete assessment of the sustainability of an area. The indicators in the national census can be considered 'profile' indicators in that they only provide a 'snapshot in time' of the conditions of a CSD. On the other hand, most social indicators

can be labeled 'process' indicators which measure things like community capacity, community well-being, and community resilience (Beckley *et al*, 2002). Beckley *et al* (2002) stress that a full description of the economic and social dimensions of an economy can only be achieved by a combination of quantitative and qualitative indicators.

A simpler task would be to expand the set of variables by further exploiting the Canadian census. Time did not permit the inclusion of every possible indicator in this study. However, additional variables could be incorporated into the database to enhance the sustainability assessment of the existing income, equity, and resilience categories. This continued use of the census celebrates the fact that a standardized suite of indicators exist at the community level on a broad national scale. Often, community level sustainability assessment is ideal and the preferred scale, but the challenge is the availability of suitable information with which to calculate or describe the indicators of interest. The expansion of the database, as well as the present analysis would remove some of this obstacle so that communities can be compared to one another through the use of the census indicators. Due to the significant interdependencies between communities, some may argue that a region is a more accurate level at which to study and assess sustainability. It is then necessary to use standardized measurements to enable comparisons between communities for aggregation up to the regional level (Force and Machlis, 1997). Even if this is the case, this database and its potential for expansion provides a quick and easy way to compare regional attributes in sustainability assessments. The one downfall is that data suppression prevents some communities from being included in these types of sustainability assessments.

However, the census is not infallible. Most information is not available at the individual level. Thus, sometimes adjustments have to be made to generate usable information. These issues were dealt with in the present study. Therefore, valuable information and statistics managed to be generated. This could serve as an example. If more studies exploit the census for information, it would serve to enhance our understanding of sustainability at the community, regional, provincial, and national level. There also exists the need for additional indicators, such as augmented income and social indicators (as mentioned above) to enhance community level assessment of sustainability. This illustrates the need to allocate sufficient financial and labour resources to generate the necessary information, and to continue this generation to allow for the examination of new temporal trends.

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APPENDIX A: DATA ISSUES

A.1. Exclusion of 1981 Census Data

Although this thesis examines only the 1986, 1991, and 1996 censuses, it would have been ideal to have a fourth year in the database to allow for lags in the models. Since the 2001 census data was not yet available, the 1981 census was explored as a possible addition to the database. However, after selecting the desired variables for examination from the other three census years, it was discovered that 1981 was missing some of the same key variables. Also, the available data source for the 1981 data used the enumeration area as its geographic area. Thus, any data extracted would have to amalgamated up to the Census Subdivision (CSD) level. There would most certainly be rounding errors in the aggregation due to data suppression at this level of geography. Thus, only the three remaining census years were used for data analysis.

A.2. Census Subdivision (CSD) Definition

The main level of geography examined in this study is the census subdivision (CSD). A CSD is either a municipality (as determined by provincial legislation), or its equivalent (unorganized territories, Indian settlement or reserves). In Newfoundland, Nova Scotia, and British Columbia, a CSD can also be a geographic area created by Statistics Canada (also equivalent to a municipality) for the purpose of census data collection (Statistics Canada, 1999).

A.3. Missing CSDs from either Census Profiles 2A or 2B

The census data is gathered under two profiles: 2A which is data collected from 100% of the population, and 2B (20% of the population). However, remote areas and Indian reserves have data collected from 100% of the population. The data from Profile 2B in other areas is weighted up to provide estimates for the whole population (Statistics Canada, 1999). When aggregating the 2A and 2B profiles for each year, it was discovered that for 1991 there were 21 CSDs that were not common to both profiles. Thus, these CSDs had to be removed from the datasets for 1986, 1991, and 1996. Below is a table detailing these CSDs.

Appendix A, Table 1: Missing CSDs

List of CSDs found in 1991 2A, but not 2B	*List of CSDs found in 1991 2B, but not 2A*
Sally's Cove (1009037) COM 00000	Terra Nova (1007040) COM 00000
Queens, Royalty (1102018) LOT 00010	Goodwater (4702036) VL 00000
Manitoulin, Unorganized, Mainland (3551091) UNO 01020	Carmichael (4704056) VL 00000
Fife Lake (4703008) VL 00000	Waldron (4705061) VL 00000
St. Victor (4703027) VL 00000	Evesham (4713052) VL 00000
Meyronne (4703049) VL 00010	Lakeview (4811042) SV 00010
Netherhill (4713004) VL 00000	Willowbrook (4709018) VL 00000
Birchcliff (4808023) SV 01000	
Parkland Beach (4808042) SV 01000	
Grandview (4811004) SV 00000	
Mewatha Beach (4813045) SV 00040	
Telegraph Creek 6 (5949826) R 01020	
Duff (4705068) VL 00000	
Success (4708036) VL 00010	

A.4. Consumer Price Indexes by Province for 1986, 1991, and 1996

When standardizing the three census years of data, it was necessary to adjust each monetary variable to constant dollars using the Consumer Price Index (CPI). Provincial

CPI's for 1986, 1991, and 1996 were used to adjust each group of CSDs in each year. Below is the table of provincial CPI's by year, with a base year of 1992.

Appendix A, Table 2: CPI numbers by province and year

Geography	1986	1991	1996
Canada	78.1	98.5	105.9
Newfoundland	81.9	99.0	106.0
P.E.I.	78.8	99.2	105.2
Nova Scotia	79.7	99.3	105.6
New Brunswick	80.0	99.3	104.9
Quebec	77.7	98.2	103.4
Ontario	77.5	99.0	105.9
Manitoba	78.9	98.6	109.2
Saskatchewan	78.8	99.0	108.9
Alberta	79.1	98.5	107.3
British Columbia	78.6	97.4	108.9
Yukon	81.2	99.1	107.5
N.W.T.	80.3	99.0	108.2

- Statistics Canada (2001)

A.5. Statistics Canada Random Rounding and Data Suppression Rules

When evaluating statistics in the Canadian census, it is important to keep in mind Statistics Canada's procedure of random rounding and area suppression. Although the practices listed here can be applied generally to the data, each year's suppression rules may slightly vary. The practice of random rounding is applied to all census variables, except population counts. Thus, any number in tabulation, including totals, are rounded up or down to a multiple of five, and in some cases ten. Random rounding protects the confidentiality of survey respondents (so that none of the data can be traced to a specific individual), yet does not add significant error to the census data. Area suppression also exists for the purpose of protecting confidentiality. Statistics Canada removes all characteristic data for geographic areas with populations below a particular size. Thus, all data in CSDs with less than 40 people is suppressed, and if the data contains income

distribution and related statistics, this is suppressed in CSDs with less than 250 people. Anytime area suppression is used, the suppressed data is always included in higher, aggregated totals for the variables (Statistics Canada, 1999). Since random rounding and area suppression are in effect in small communities, the census data, including employment numbers are affected. Statistics Canada (1999) warns that small cell counts may suffer a considerable distortion from random rounding. Given that the employment numbers are the basis for the forest dependence calculations, these procedures can affect the level of forest dependence in these small communities. One way to minimize distortions from random rounding is to use custom tabulation numbers, rather than census data. These tabulations aggregate data from individual census records, where rounding does not occur until aggregation is complete. However, due to budget and time constraints, the Canadian census was the source for most of the variables used in this study. Statistics Canada also warns that the resulting estimates are subject to various errors that can occur while compiling the census data. These errors include coverage errors, non-response and response errors, processing errors, and sampling errors. For information on these errors, the Statistics Canada Census Dictionary for any year in question can be consulted (Statistics Canada, 1999).

A.6. Industry Categories at the "S" level for 1980 Standard Industrial Classification System

The following is a list of the industry categories at the "S" level according to Statistics Canada. All of the employment and average income data was standardized to coincide with this list:

Appendix A, Table 3: Industry Categories at the "S" level according to 1980 Standard Industrial Classification

Division A	Agricultural and related service industries
Division B	Fishing and trapping industries
Division C	Logging and forestry industries
Division D	Mining (incl. milling), quarrying, & oil well industries
Division E	Manufacturing industries
Division F	Construction industries
Division G	Transportation and storage industries
Division H	Communication and other utility industries
Division I	Wholesale trade industries
Division J	Retail trade industries
Division K	Finance and insurance industries
Division L	Real estate operator and insurance agent industries
Division M	Business service industries
Division N	Government service industries
Division O	Educational service industries
Division P	Health and social service industries
Division Q	Accommodation, food and beverage service industries
Division R	Other service industries

- Statistics Canada (2000)

A.7. Reasons for the Largest Group of Missing Data

As noted earlier, the particular source for the 1986 and 1991 average incomes was missing 787 CSDs and their incomes for 1991. There are three possible reasons for the missing CSDS. First, the source reported income data, which is collected from census profile 2B (a 20% sample). Therefore, a CSD's income data was suppressed if the non-institutional population was below 250 people. Thus, it is possible for a CSD to have a population over 250, with suppressed income data. This is due to the fact that when the census reports a CSD's population, it usually is reported from the 100% sample showing the total population of the CSD. Secondly, some of the missing CSDs could have been Incompletely Enumerated Indian Reserves, which would suppress their data. Last of all,

suppression of CSDs can occur if the data tabulations show a global non-response rate of 25% or more. The global non-response rate refers to the percentage of required responses left unanswered by respondents (Sather, 2002).

A.8. National Import and Export Data Source

In the forest dependence calculations, the province's share of employment income in each industry is weighted by the proportion of national output minus net exports to show the amount of output needed to meet domestic consumption. While national output tables were readily available, the national import and export data was difficult to find. Statistics Canada categorizes industry data by 3 levels: "L" which is the link level, "M" which is the medium level, and "S" which is the small level, with increasing aggregation of industry categories in each. All of these levels are created from an even more disaggregated set of categories than "L" which is "W" the worksheet level. Although Statistics Canada publishes documents that list national imports and exports at the "L" level, they cannot be easily collapsed into the "S" level format (the 18 industries that this study has been using). This is because "S", "M", and "L" are not linked to each other, but they are separately linked to the "W" level of categorization. Thus, the national import and export data at the "L" level had to be linked back to the "W" level, from which the national imports and exports at the "S" level could then be derived (Statistics Canada, 1998). This process required a custom tabulation from Statistics Canada (2002).

A.9. Standardization of CSDs from 1986-1996

It was necessary to take a few steps to ensure each CSD could be compared to itself across the three census years. The first set of necessary changes only applied to the province of Quebec. After the 1986 census, Statistics Canada and Quebec agreed that the 'municipalitiés régionales de comté' (MRC) would be recognized as the census division level of the Standard Geographical Classification hierarchy in Quebec for 1991. The MRC geographic units are used as the current system of regional administration in the province. Since the MRC boundaries were vastly different than the 1986 census division boundaries, an entire revision of all Quebec SGC codes was necessary at the CSD level (Statistics Canada, 1992). While changing the SGC codes, name changes were ignored for now, and it was discovered that some CSDs had been joined to make one new CSD. Between 1991 and 1996, there were 101 CSD dissolutions within Quebec. This high number was meant to reflect the provincial government move to combine some municipalities to be one regional municipality, which was an effort to cut costs (Statistics Canada, 1999). Thus, in these cases, all of the variables from the two communities had to be combined. If the variables could not be simply added together, a weighted average was performed using the population in each CSD. In three separate instances, a CSD was missing some data so the weighting average for the variable was computed only from the other CSD(s). Also, 8 CSDs had to be entirely deleted, as they were not found in the Quebec SGC code changes file.

At the same point in time, Statistics Canada reorganized a few census divisions in British Columbia, which resulted in changes to a small number of CSDs. The SGC codes for these CSDs were revised to reflect these changes (Statistics Canada, 1992).

In standardizing the initial data extracts from the Canadian census, it was recognized that there have been numerous changes to CSD boundaries, names, codes, and types across Canada from 1986-1996. Although these changes were not dealt with at the beginning of the compilation of the database, they must be addressed in order to compare the three years of census data. The CSD changes originate from three sources: provincial legislation, Indian and Northern Affairs Canada, and Statistics Canada. The changes are necessary either to make data collection more efficient, or because of change and growth in urban areas (Statistics Canada, 1999). Recognition and application of these changes is important as it further standardizes the database and allows more CSDs to match up across all three years. Thus, it can prevent a CSD from being removed from the database due to missing data points. Across the ten years of study, there were two sets of changes: between 1986 and 1991, and between 1991 and 1996 (Statistics Canada, 1992, 1997). The changes are grouped into 10 coded categories. Codes 1, 2, 4, and 7 represent the creation of a CSD, a name change, dissolution of a CSD, and a SGC code change respectively (Statistics Canada, 1992). Changes to CSDs that fell under this set of codes were applied to the data. However, the creation of a new CSD (code 1) was only followed if all of the component CSDs were completely dissolved (code 4). Thus, if CSD was partially annexed (codes 5 and 6) to create a CSD, the change was ignored. If the component CSDs were completely dissolved, their variables had to be added together to create the new CSD. Thus, their respective populations could be cross-referenced against the new CSD's population in the next census year. Most often the populations matched exactly. However, if they were different, the code changes were only implemented if the population difference was less than 200 people. The 6 codes outside

of 1, 2, 4, and 7 represent the most numerous changes and characterize partial annexations and boundary revisions. These latter changes could not be applied to the data as the changes were too numerous and detailed for a group of over 5000 CSDs. However, this exclusion should have little effect on the analysis as these annexations and revisions usually involve very small areas and populations (Statistics Canada, 1992).

A.10. Share of CSDs by Province Represented in the Final Dataset for Study

After making the necessary CSD deletions from the dataset, the final dataset contained 4202 CSDs across Canada. The following table shows the percentage of CSDs from each province that were retained for the final dataset. Since the three years of CSDs were standardized with 1996 being the final year, the percentages were calculated using the number of CSDs in each province according to the 1996 Census (Statistics Canada, 1999).

Appendix A, Table 4: The Share of CSDs by Province in the Study's Final Dataset

Province	Share of CSDs	Percentage (%)
Newfoundland	287/381	75.3
Prince Edward Island	93/113	82.3
Nova Scotia	91/110	82.7
New Brunswick	246/283	86.9
Quebec	1349/1599	84.4
Ontario	772/947	81.5
Manitoba	240/298	80.5
Saskatchewan	561/970	57.8
Alberta	273/467	58.5
British Columbia	241/713	33.8
Yukon territory	7/35	20.0
Northwest Territories	42/68	61.8
Canada	**4202/5984**	**70.2**

APPENDIX B: "TESTING" THE KUZNETS HYPOTHESIS

B.1. Theory Behind the Kuznets Hypothesis

An analysis of factors affecting the Gini coefficient can be found in Li, Xie, and Zou (2000). The authors test the Kuznets hypothesis. The hypothesis (as it pertains to their study) is that a country's income inequality is low at low income levels, but will increase over time as a country's overall income level rises in conjunction with economic growth. Under this hypothesis, an inverted U-curve depicts this relationship between income distribution and the Gini coefficient. Since the country's income level is low, but increasing over time, the Kuznets hypothesis is typically applied only to low development (Third World) countries. Due to the fact that existing empirical studies testing this hypothesis have given contradictory results, Li *et al* (2000) were interested in testing whether the hypothesis would hold with their particular dataset. The time series dataset contained 84 countries with 583 observations for the period 1950-1992. Due to the scattered nature of the income distribution data (as measured by the Gini coefficient), the authors pooled the countries together to produce three sample sizes: a full sample with all 84 countries, a high income level sample with 24 countries, and a middle-to-low income level sample with 60 countries. The first specification Li *et al* (2000) used was:

$$GINI_{it} = \alpha_i + \beta_i Y_{it} + \gamma_i (Y_{it})^2 + u_{it} \qquad [29]$$

where i = country index, t = time index, and Y = real per capita income. Since the Kuznets hypothesis can be empirically verified if the coefficient on Y^2 is negative, the authors found only weak evidence of the hypothesis in the middle-to-low-income sample only (Y^2 coefficient was negative, but not significant).

Li *et al* (2000) used a second specification to control for the effects of government spending:

$$GINI_{it} = \alpha_i + \beta_i Y_{it} + \gamma_i (Y_{it})^2 + \tau_i G_{it} + u_{it} \quad [30]$$

where G = government spending as a share of GDP. However, the results did not vary much from those in equation [29]. To test whether the results were subject to functional form changes, the authors re-estimated equations [29] and [30] using the natural logarithm of Y. The only substantial difference from the original results was that the transformed equation [30] did show a statistically significant, inverted U-curve relationship between income distribution and income level in the middle-to-low-income sample.

Li *et al* (2000) then tested the robustness of the estimation results (for the Gini coefficient and income level) to see if they would be sensitive to the inclusion of additional, related regressors. The extra variables were:

Openness: total trade value (of imports and exports), as a percentage of GDP
Population Growth
Financial Development: (M^2/GDP)
Terms of Trade Shocks: ($\Delta \ln P_x - \Delta \ln P_M$) where P_x, P_M = export/ import unit price

The results from the sensitivity analysis provided overall support for the results from the original and log-transformed specifications. On the whole, the authors found that the Kuznets hypothesis did not hold for their dataset when a full sample of all countries was examined. However, they did find some evidence that it held for the middle-to-low-income sample (Li *et al*, 2000).

B.2. Model Development with Study's Census Data

Since Canada is a relatively rich nation, it is inappropriate to test the Kuznets hypothesis directly. However, we can use test whether there is a similar positive, then negative relationship between income inequality (Gini coefficient) and the income levels in a CSD over time. This was performed with the three years of census data to develop empirical models with the Gini coefficient as the dependent variable. Since the dataset in this thesis is at the CSD level, median household income and average household income were chosen to represent income. The empirical models developed are:

$$GINI_{it} = \beta_1 + \beta_2 MEDHINC_{it} + \beta_3 [MEDHINC]^2_{it} + \beta_4 PROVEMP_{it} + \beta_5 D_{1t} + \ldots + \beta_{14} D_{10t} + \mu_i + \epsilon_{it} \quad [31]$$

$$GINI_{it} = \beta_1 + \beta_2 AVGHINC_{it} + \beta_3 [AVGHINC]^2_{it} + \beta_4 PROVEMP_{it} + \beta_5 D_{1t} + \ldots + \beta_{14} D_{10t} + \mu_i + \epsilon_{it} \quad [32]$$

where AVGHINC = average household income. These models also explore a semi-log functional form to test the robustness of the linear model results. Both equations [31] and [32] are re-estimated again (as models [33] and [34]) with the logarithmic form of each income variable replacing the linear terms.

B.3. Estimation Results

The results from the four models are shown in Table 1 of this appendix. The relationship we are looking for can be empirically verified by a positive and significant coefficient on the single income variable, and a negative and significant coefficient on the squared income variable (Li *et al*, 2000). As seen in Table 1, the results from regressions [31] and [32] do not show this result. However, the regressions were run again in a semi-logarithmic form with the linear income variables replaced by their logarithmic

counterpart. The results from these regressions (models [33] and [34]) show that only the semi-logarithmic form of AVGHINC exhibits the inverted U relationship between income inequality and the CSD's income level. Thus, at lower levels of average household income, income inequality (as represented by the Gini coefficient) is low. However, as average household income increases over time, income inequality also increases. Whether this relationship is found or not is not important. It merely allows us to state whether the inverted U-curve relationship (whose theory is taken from the Kuznets hypothesis) is found between the income variables and Gini coefficient for the CSDs in our study.

The other results from regressions [31] and [32] in terms of the Gini coefficient's relationship to aggregate demand and the dummy variables were robust in that the results corresponded to those found in regression [23].

The adjusted R^2 values were low for all of the models in this set. The two models with MEDHINC had values of 11.1%, while the models of AVGHINC had adjusted R^2 values of only 4.3% and 4.5%. Thus, the variation in a CSD's Gini coefficient is highly dependent on variables other than income. However, the addition of other variables in equation [23] did little to increase the adjusted R^2 value (11.5%). Thus, other factors outside of FORDEP, TEEXP, DIV, PROVEMP and UNEMPR are responsible for the variation in income distribution in a CSD. This topic deserves further study.

Appendix B, Table 1: Parameter Estimates (Standard Error) "Testing" the Kuznets Hypothesis with Census Data 1986-1996

	Dependent Variable = Gini			
Independent Variables	[31]	[32]	[33]	[34]
Intercept	0.365** (0.0127)	0.328** (0.0131)	0.330** (0.0132)	0.268** (0.0157)
MEDHINC†	-0.0219** (0.00241)			
$(MEDHINC)^2$	-0.000179 (0.000305)			
Log(MEDHINC)†			0.0144 (0.0102)	
$[Log(MEDHINC)]^2$			-0.0399** (0.00445)	
AVGHINC†		-0.00810** (0.00193)		
$(AVGHINC)^2$		-0.000319* (0.000190)		
Log(AVGHINC)†				0.0822** (0.0147)
$[Log(AVGHINC)]^2$				-0.0470** (0.00555)
PROVEMP†	0.000132** (0.0000227)	0.000116** (0.0000238)	0.000132** (0.0000227)	0.000117** (0.0000238)
Nfld	0.0403** (0.0115)	0.0433** (0.0121)	0.0398** (0.0115)	0.0436** (0.0121)
PEI	0.0534** (0.0124)	0.0524** (0.0130)	0.0531** (0.0124)	0.0518** (0.0130)
NS	0.0673** (0.0117)	0.0695** (0.0122)	0.0671** (0.0117)	0.0693** (0.0122)
NB	0.0537** (0.0114)	0.0543** (0.0119)	0.0532** (0.0114)	0.0541** (0.0119)
QUE	0.0185** (0.00464)	0.0221** (0.00487)	0.0182** (0.00464)	0.0217** (0.00486)
MB	0.0585** (0.0109)	0.0642** (0.0114)	0.0581** (0.0109)	0.0651** (0.0114)
SK	0.0649** (0.0109)	0.0683** (0.0114)	0.0647** (0.0109)	0.0689** (0.0114)
AB	0.0528** (0.00908)	0.0513** (0.00952)	0.0527** (0.00908)	0.0513** (0.00951)
BC	0.0502** (0.00847)	0.0455** (0.00889)	0.0502** (0.00847)	0.0458** (0.00888)
NWT	0.0747** (0.0133)	0.0718** (0.0140)	0.0741** (0.0133)	0.0718** (0.0140)
Number of Observations	12606	12606	12606	12606
Adjusted R^2	0.111	0.043	0.111	0.045
F-test	121.28	44.59	121.55	46.59
LM-test (prob. value)	71.70 (.0000)	141.02 (.0000)	71.81 (.0000)	135.86 (.0000)
**P<0.05	*P<0.1			
† MEDHINC, AVGHINC and PROVEMP have been scaled (raw values /10,000)				